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Chowdhury et al.

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(54) **METHODS AND SYSTEMS FOR CROWD MOTION SUMMARIZATION VIA TRACKLET BASED HUMAN LOCALIZATION**

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G06K 9/62 (2022.01)
G06V 10/75 (2022.01)

(52) **U.S. Cl.**

CPC ***G06V 20/53*** (2022.01); ***G06K 9/6232*** (2013.01); ***G06K 9/6277*** (2013.01); ***G06V 10/751*** (2022.01)

(58) **Field of Classification Search**

None

See application file for complete search history.

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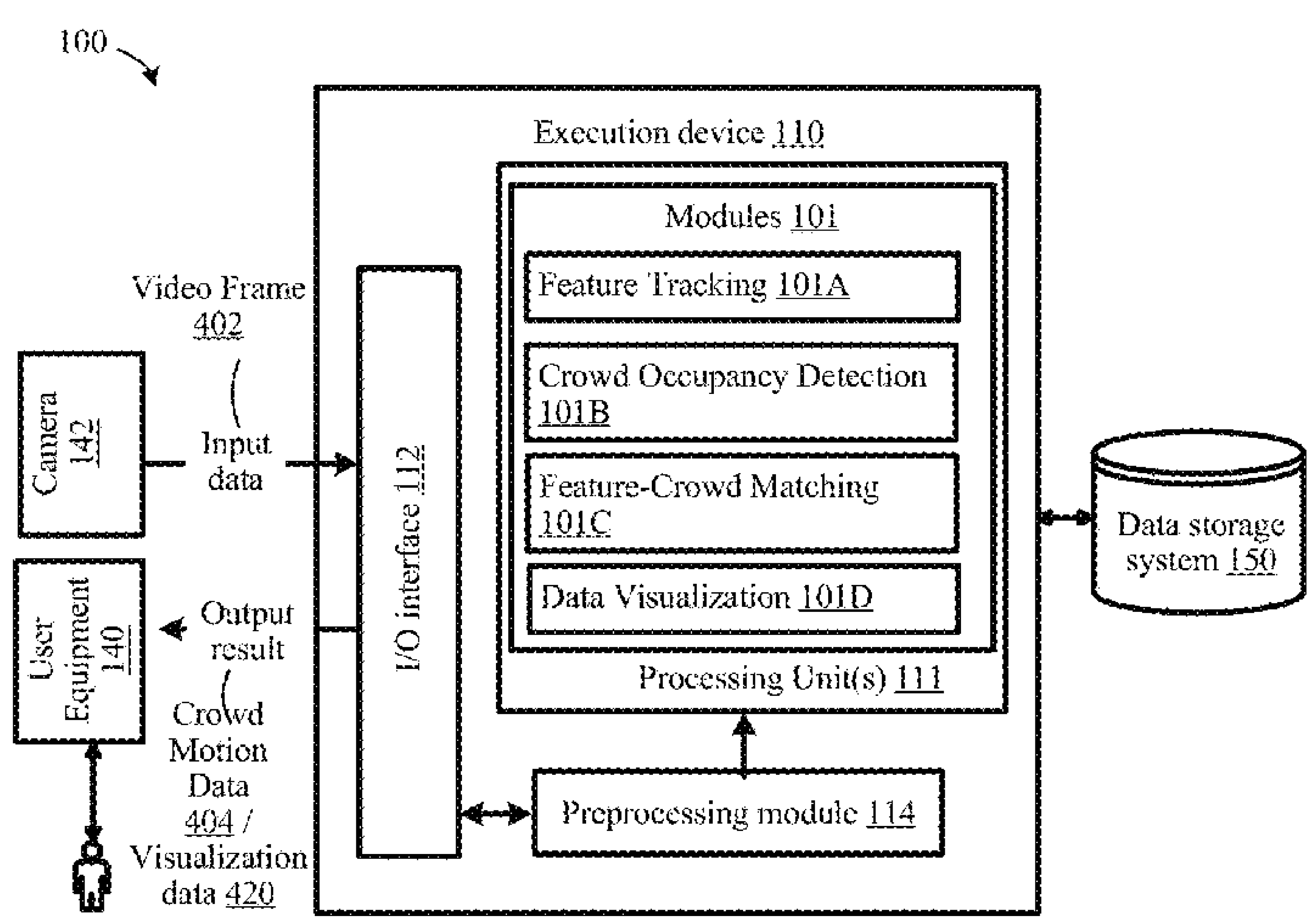
Primary Examiner — Mohammed Rachedine

(57) **ABSTRACT**

A crowd motion summarization method that provides a rich, real-time description of the crowd's characteristics from a video, such as, speed, orientation, count, spatial locations, and time. A feature tracking module receives each video frame and detects features (feature points) from the video frame. A crowd occupancy detection module receives the video frame and generates a binary crowd occupancy map having human pixel positions which indicate the human location versus non-human location, and generates a total human count of humans detected in the video frame. The feature tracking module generates feature tracking information for only those features contained in the human pixel positions which indicate the human location. In an example, the detected features are Kanade-Lucas-Tomasi (KLT) features. A feature-crowd matching module generates, using the feature tracking information and the total human count: crowd motion data. The method outputs the crowd motion data.

20 Claims, 14 Drawing Sheets



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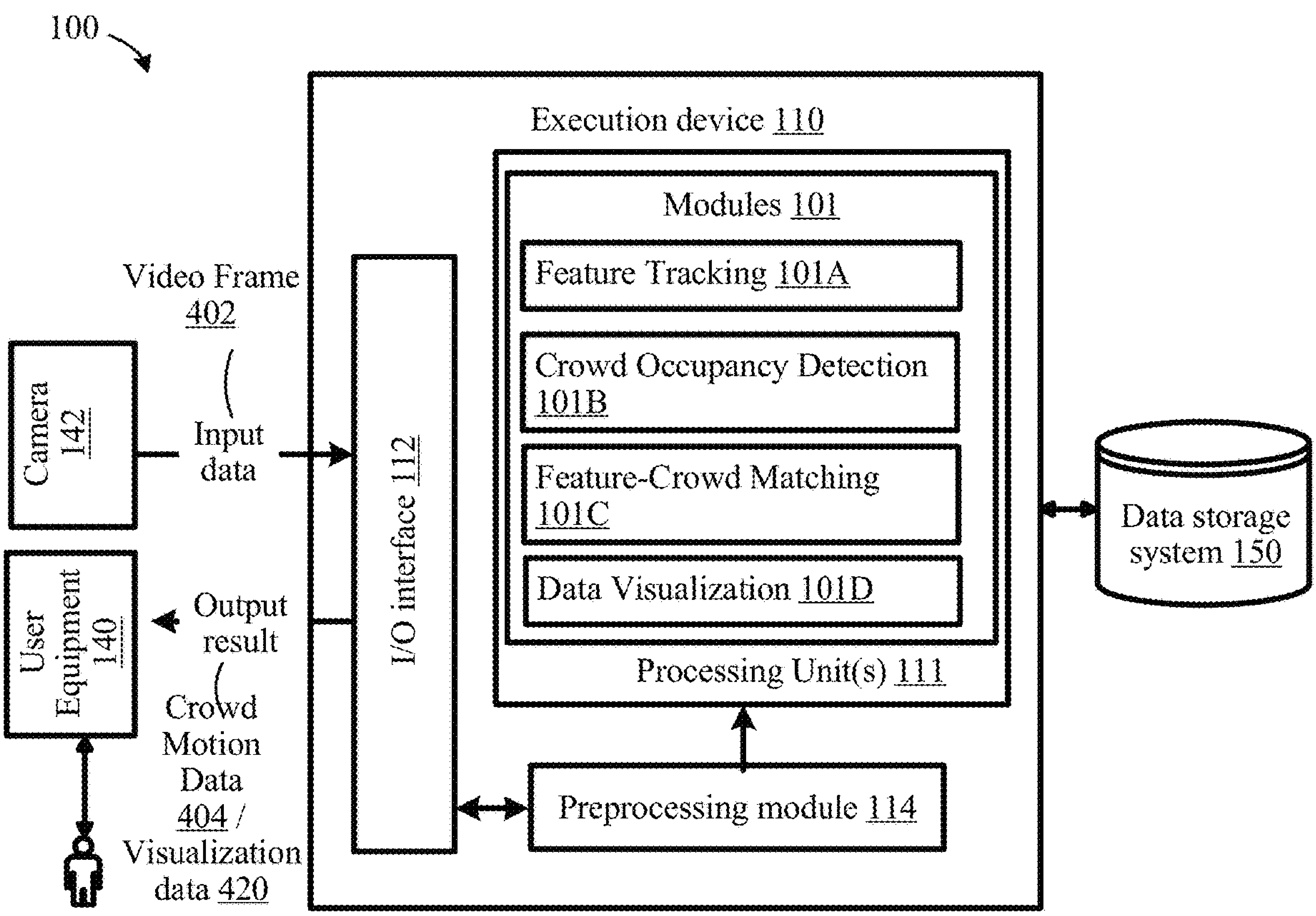

100
Execution device 110
Modules 101
Feature Tracking 101A
Crowd Occupancy Detection 101B
Feature-Crowd Matching 101C
Data Visualization 101D
Processing Unit(s) 111
Preprocessing module 114
I/O interface 112
Video Frame 402
Input data
Camera 142
User Equipment 140
Output result
Crowd Motion Data 404 / Visualization data 420
Data storage system 150

FIG. 1

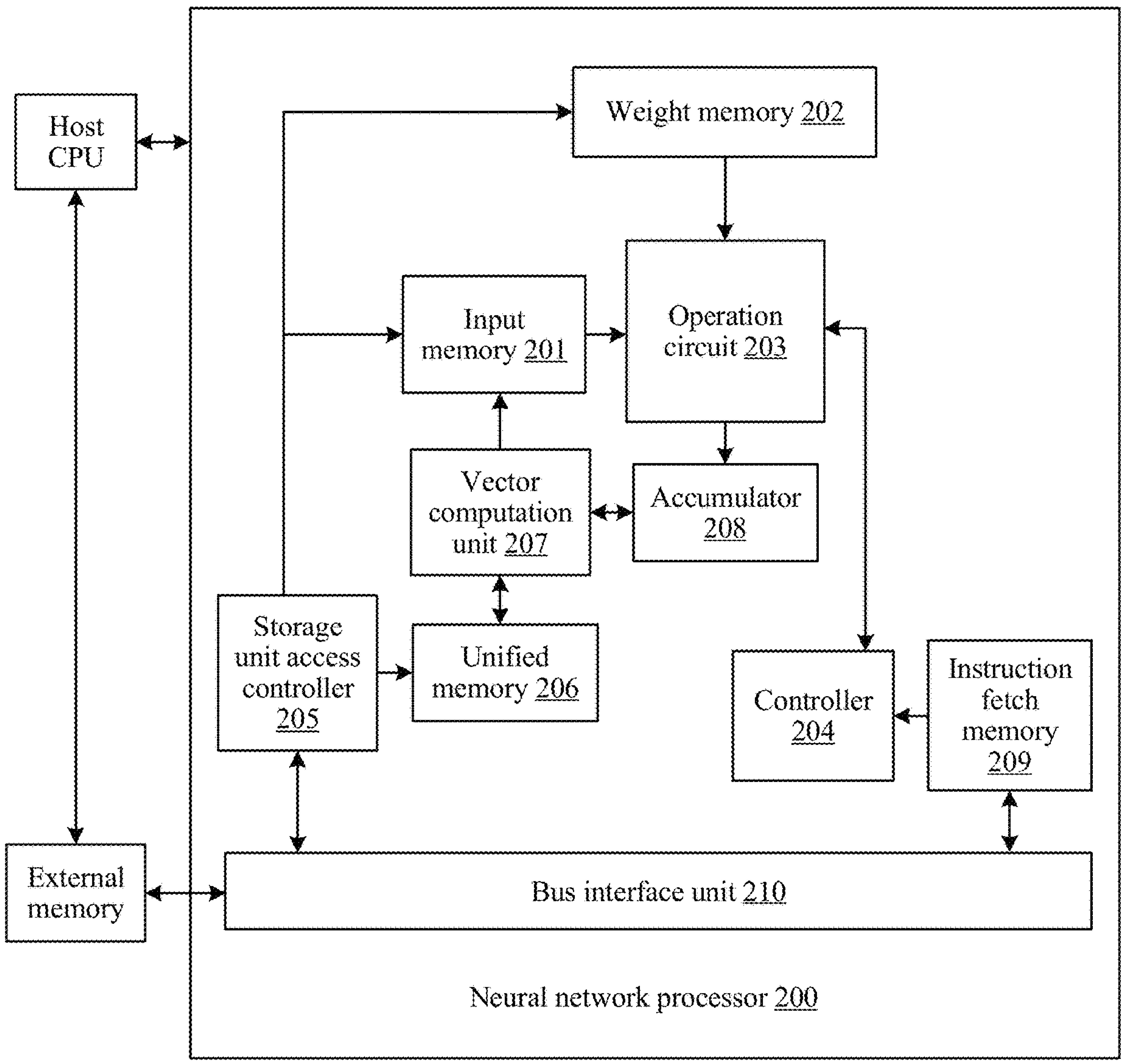

Host CPU
Weight memory 202
Input memory 201
Operation circuit 203
Vector computation unit 207
Accumulator 208
Storage unit access controller 205
Unified memory 206
Controller 204
Instruction fetch memory 209
External memory
Bus interface unit 210
Neural network processor 200

FIG. 2

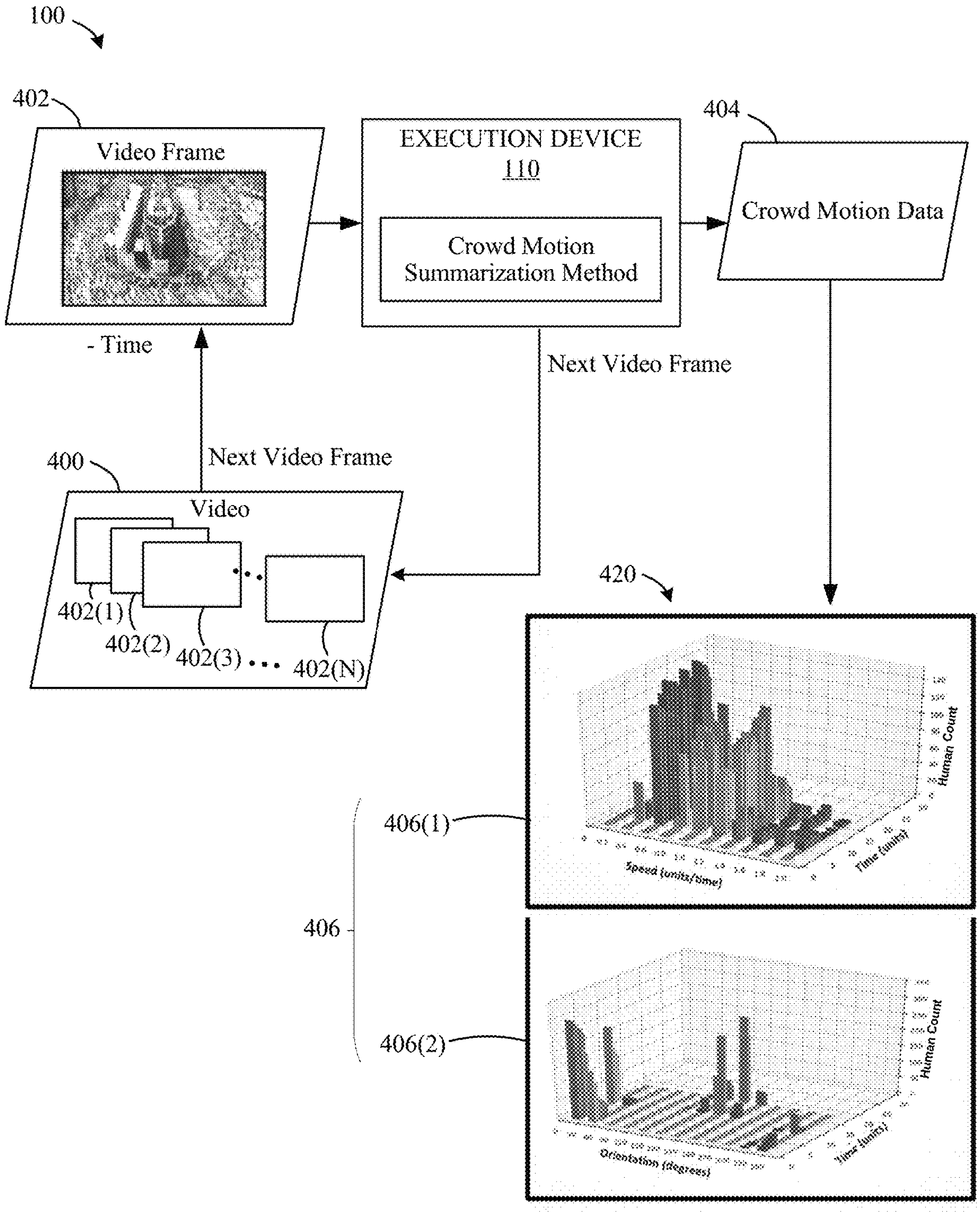

100
402
Video Frame
- Time
EXECUTION DEVICE
110
Crowd Motion
Summarization Method
404
Crowd Motion Data
Next Video Frame
400
Next Video Frame
Video
402(1)
402(2)
402(3)
402(N)
420
406(1)
406
406(2)
Human Count
Speed (units/time)
Time (units)
Orientation (degrees)

FIG. 3

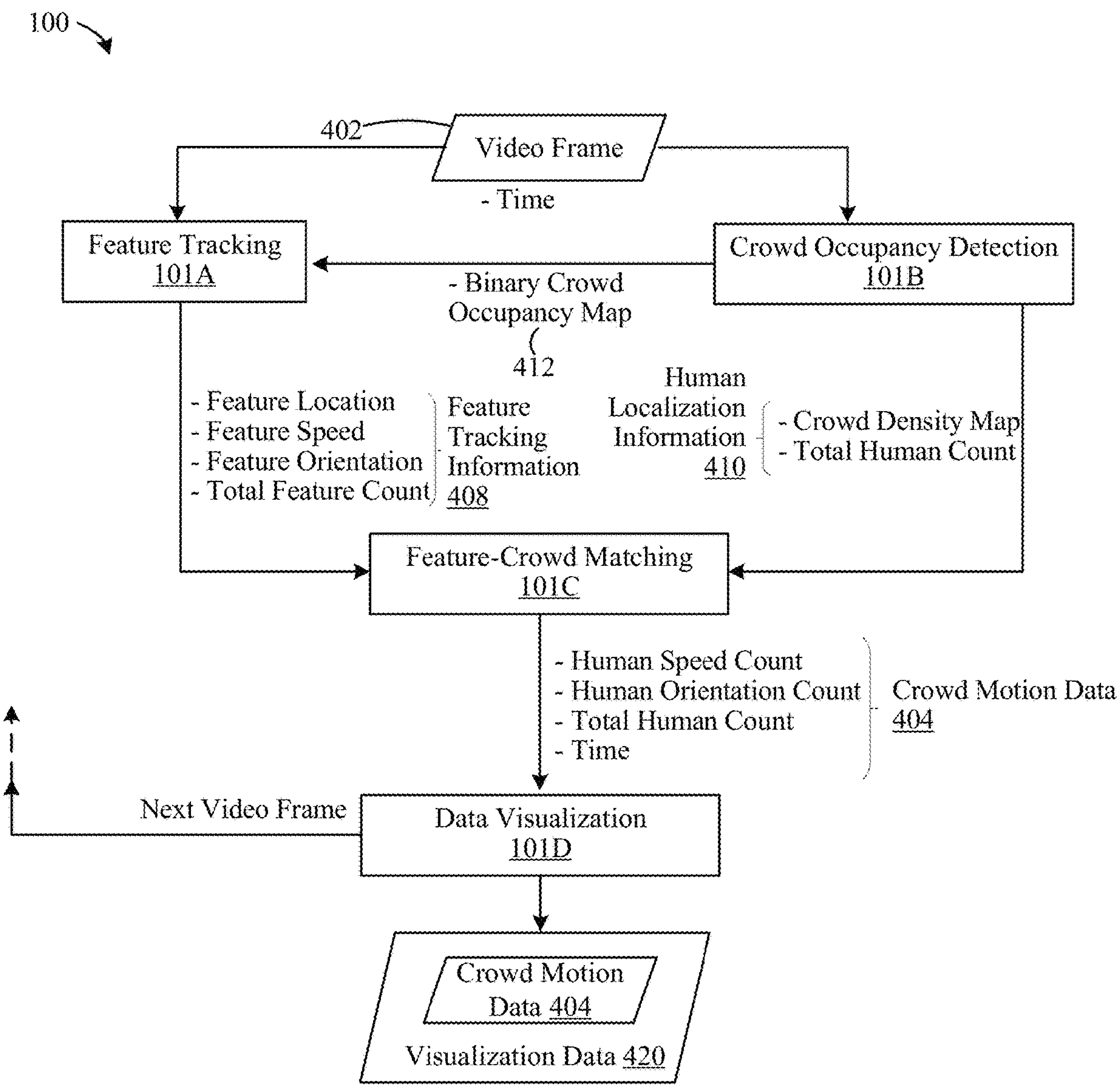

100
402
Video Frame
- Time
Feature Tracking
101A
Crowd Occupancy Detection
101B
- Binary Crowd
Occupancy Map
412
- Feature Location
- Feature Speed
- Feature Orientation
- Total Feature Count
Feature
Tracking
Information
408
Human
Localization
Information
410
- Crowd Density Map
- Total Human Count
Feature-Crowd Matching
101C
- Human Speed Count
- Human Orientation Count
- Total Human Count
- Time
Crowd Motion Data
404
Next Video Frame
Data Visualization
101D
Crowd Motion
Data 404
Visualization Data 420

FIG. 4

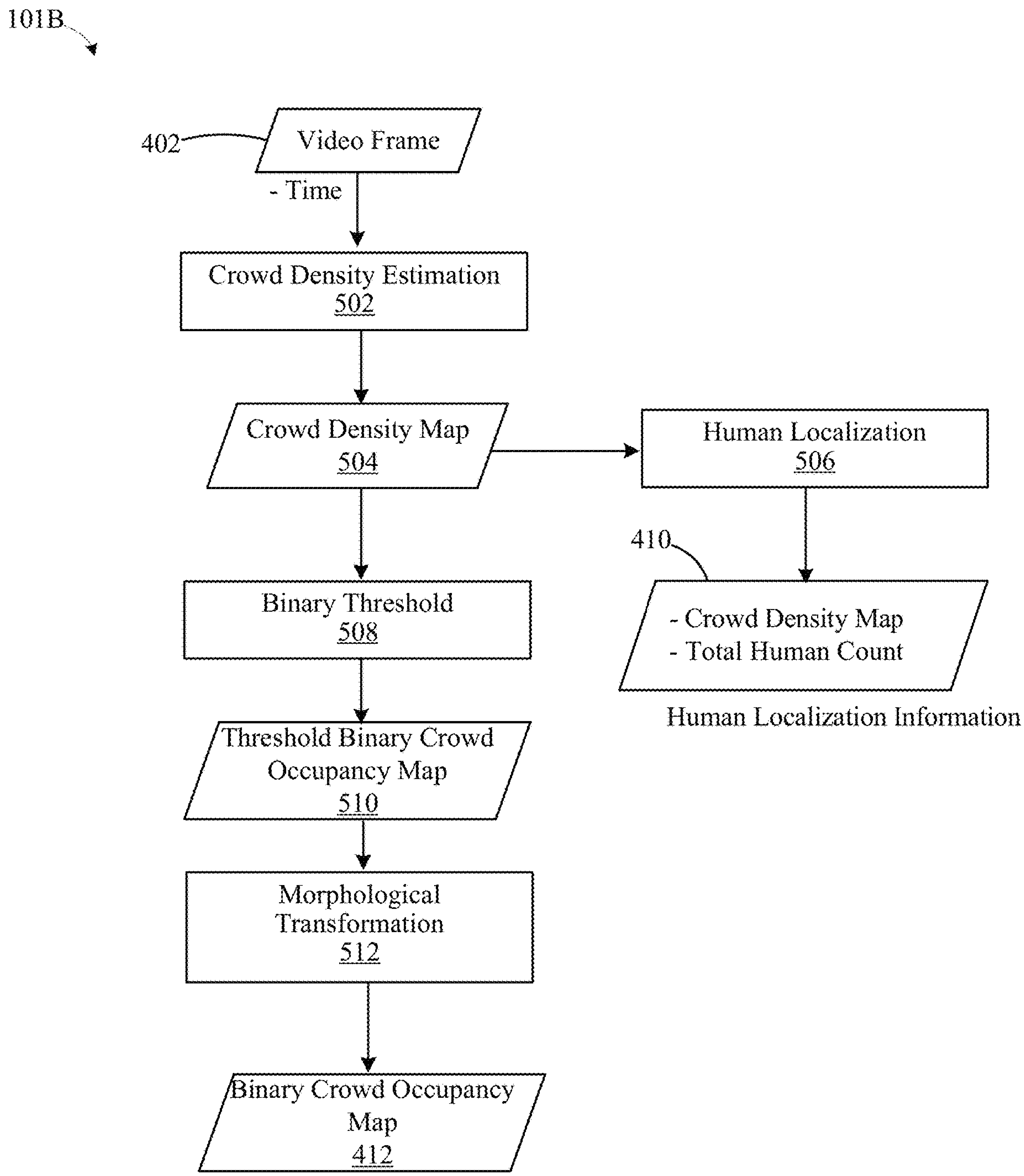

101B
402
Video Frame
- Time
Crowd Density Estimation
502
Crowd Density Map
504
Human Localization
506
410
- Crowd Density Map
- Total Human Count
Human Localization Information
Binary Threshold
508
Threshold Binary Crowd
Occupancy Map
510
Morphological
Transformation
512
Binary Crowd Occupancy
Map
412

FIG. 5

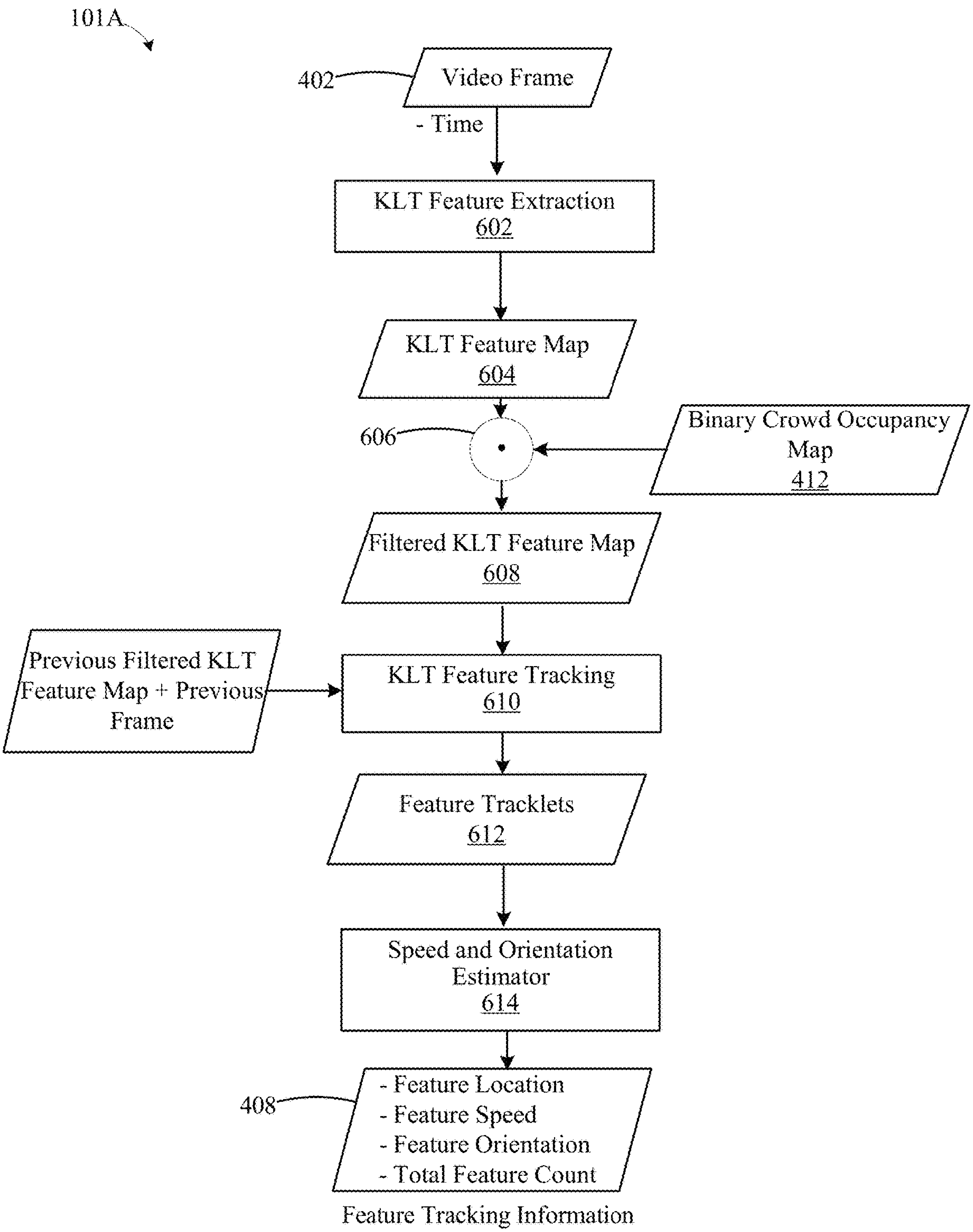

101A
402
Video Frame
- Time
KLT Feature Extraction
602
KLT Feature Map
604
606
Binary Crowd Occupancy Map
412
Filtered KLT Feature Map
608
Previous Filtered KLT Feature Map + Previous Frame
KLT Feature Tracking
610
Feature Tracklets
612
Speed and Orientation Estimator
614
408
- Feature Location
- Feature Speed
- Feature Orientation
- Total Feature Count
Feature Tracking Information

FIG. 6

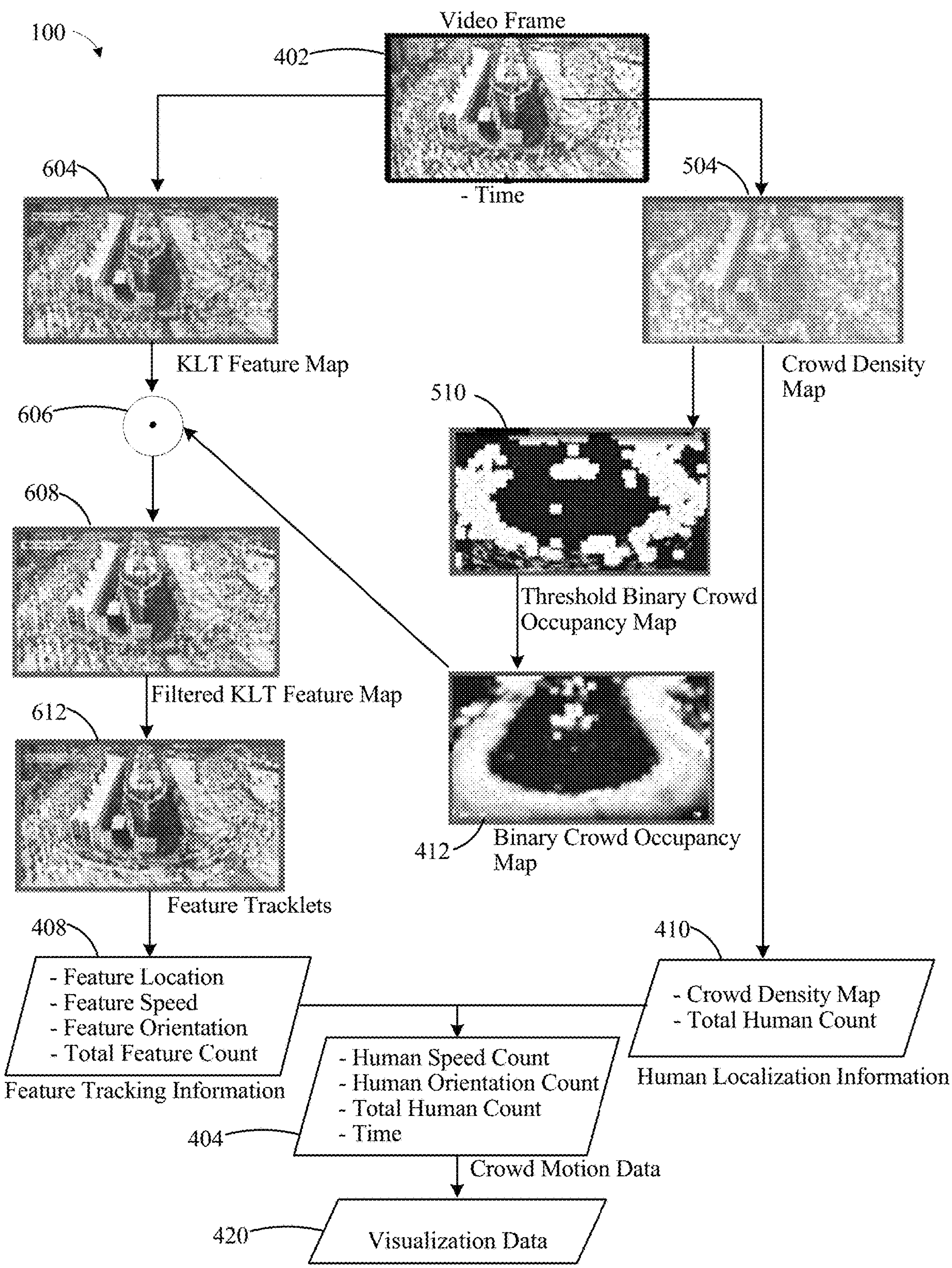

100
Video Frame
402
- Time
604
504
KLT Feature Map
Crowd Density Map
510
606
608
Threshold Binary Crowd Occupancy Map
Filtered KLT Feature Map
612
412
Binary Crowd Occupancy Map
Feature Tracklets
408
410
- Feature Location
- Feature Speed
- Feature Orientation
- Total Feature Count
Feature Tracking Information
- Crowd Density Map
- Total Human Count
Human Localization Information
- Human Speed Count
- Human Orientation Count
- Total Human Count
- Time
404
Crowd Motion Data
420
Visualization Data

FIG. 7

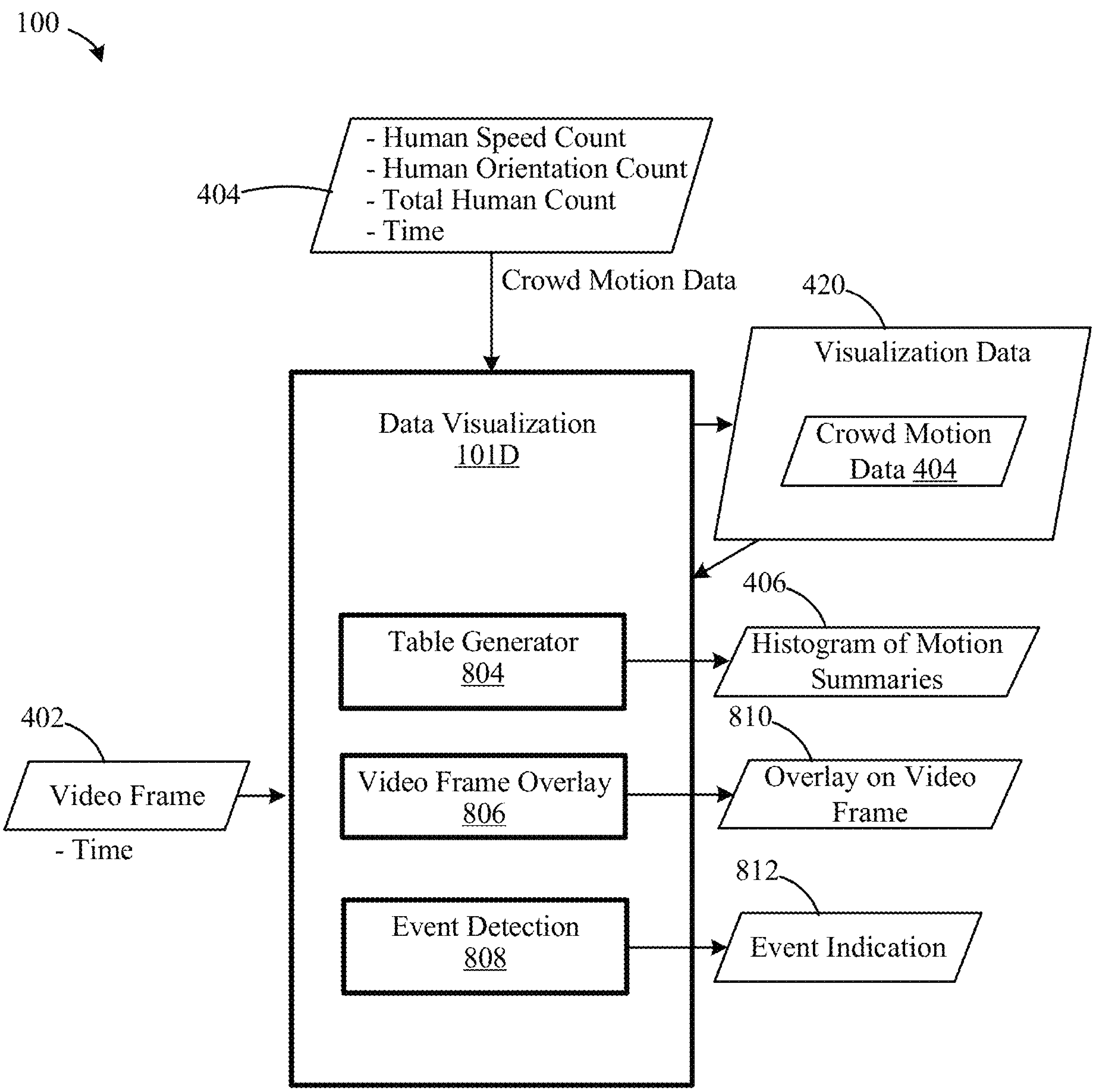

100
404
- Human Speed Count
- Human Orientation Count
- Total Human Count
- Time
Crowd Motion Data
420
Visualization Data
Crowd Motion Data 404
Data Visualization 101D
406
Table Generator 804
Histogram of Motion Summaries
402
810
Video Frame
- Time
Video Frame Overlay 806
Overlay on Video Frame
812
Event Detection 808
Event Indication

FIG. 8

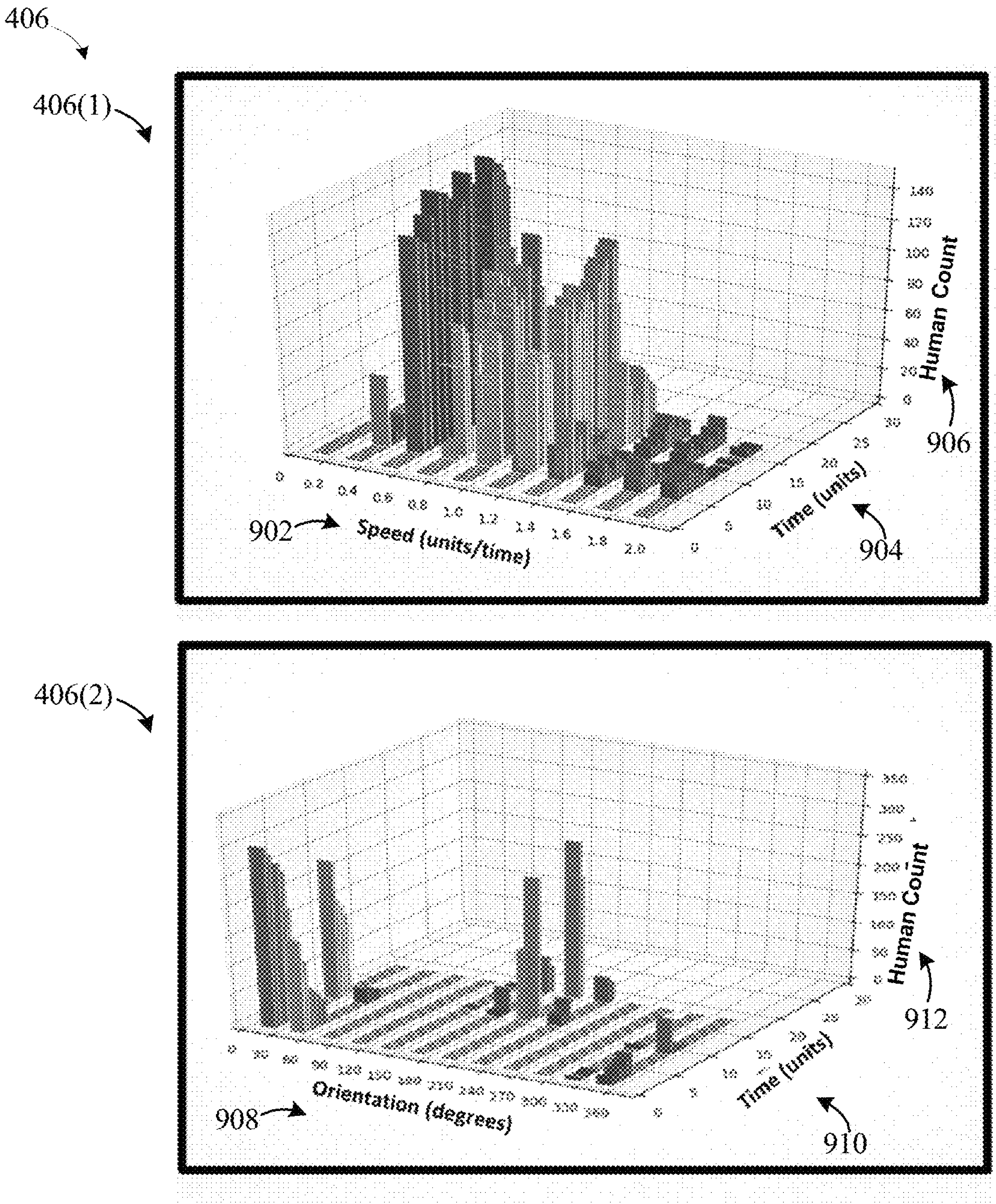

406
406(1)
Human Count
Time (units)
Speed (units/time)
902
904
906
406(2)
Human Count
Time (units)
Orientation (degrees)
908
910
912

FIG. 9

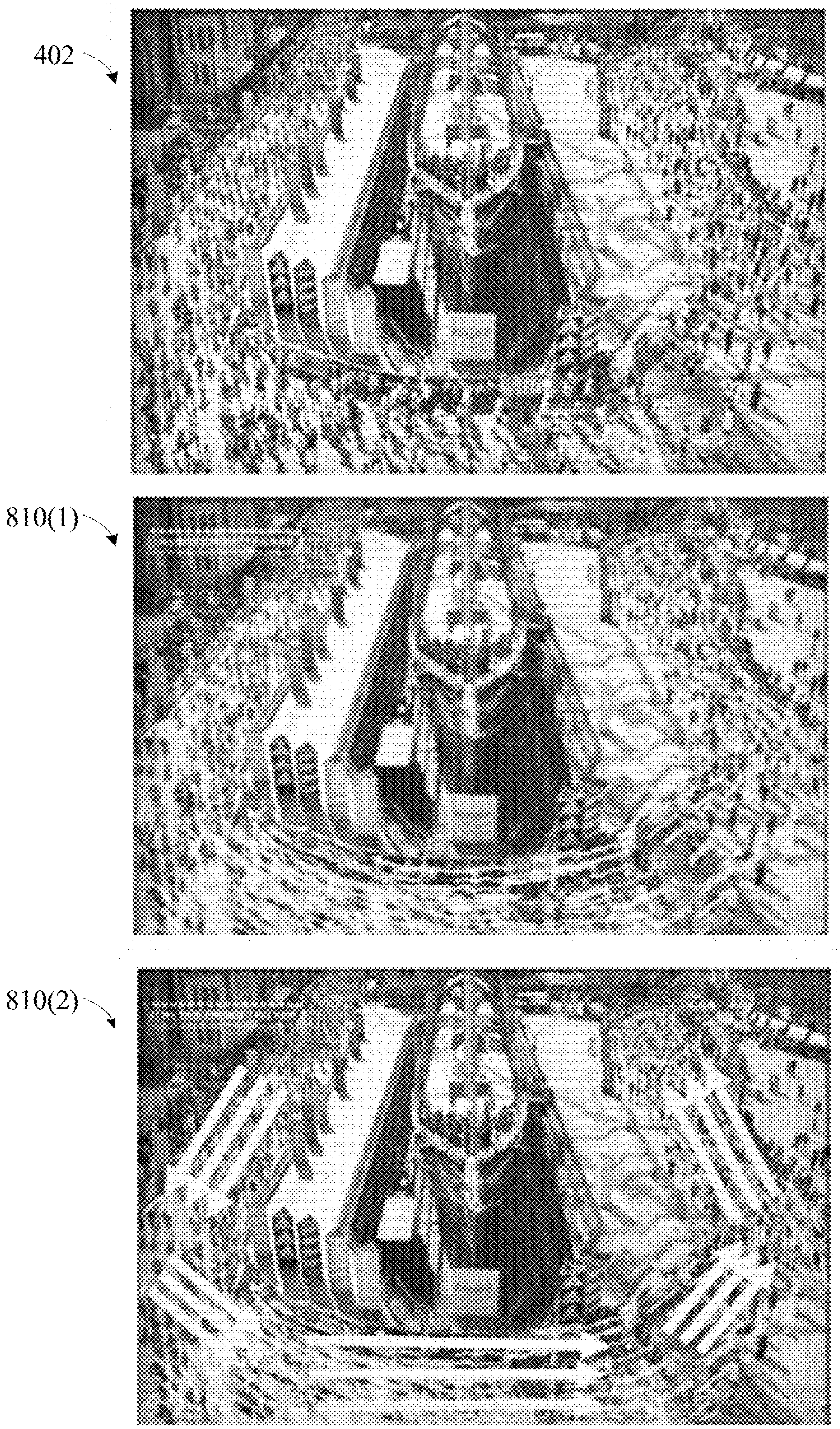
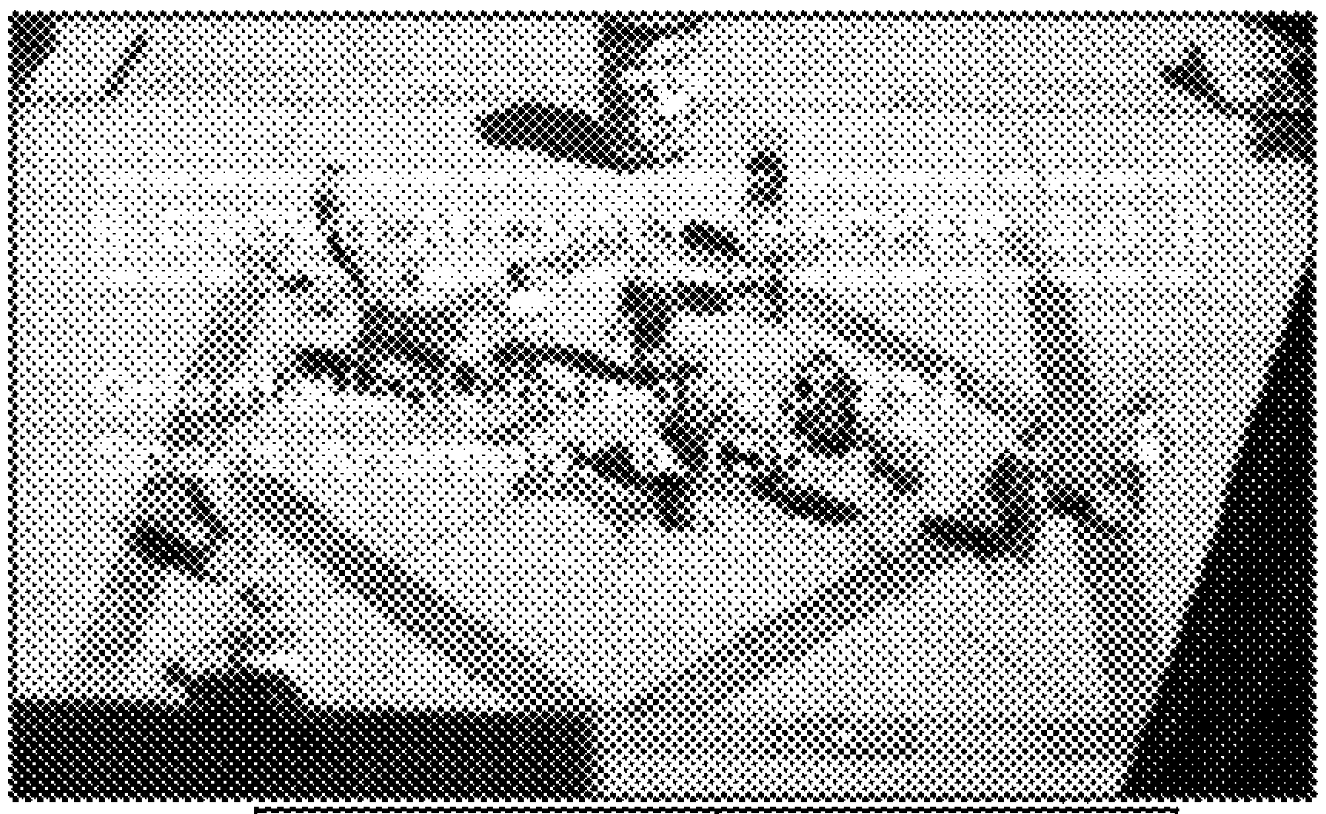


FIG. 10

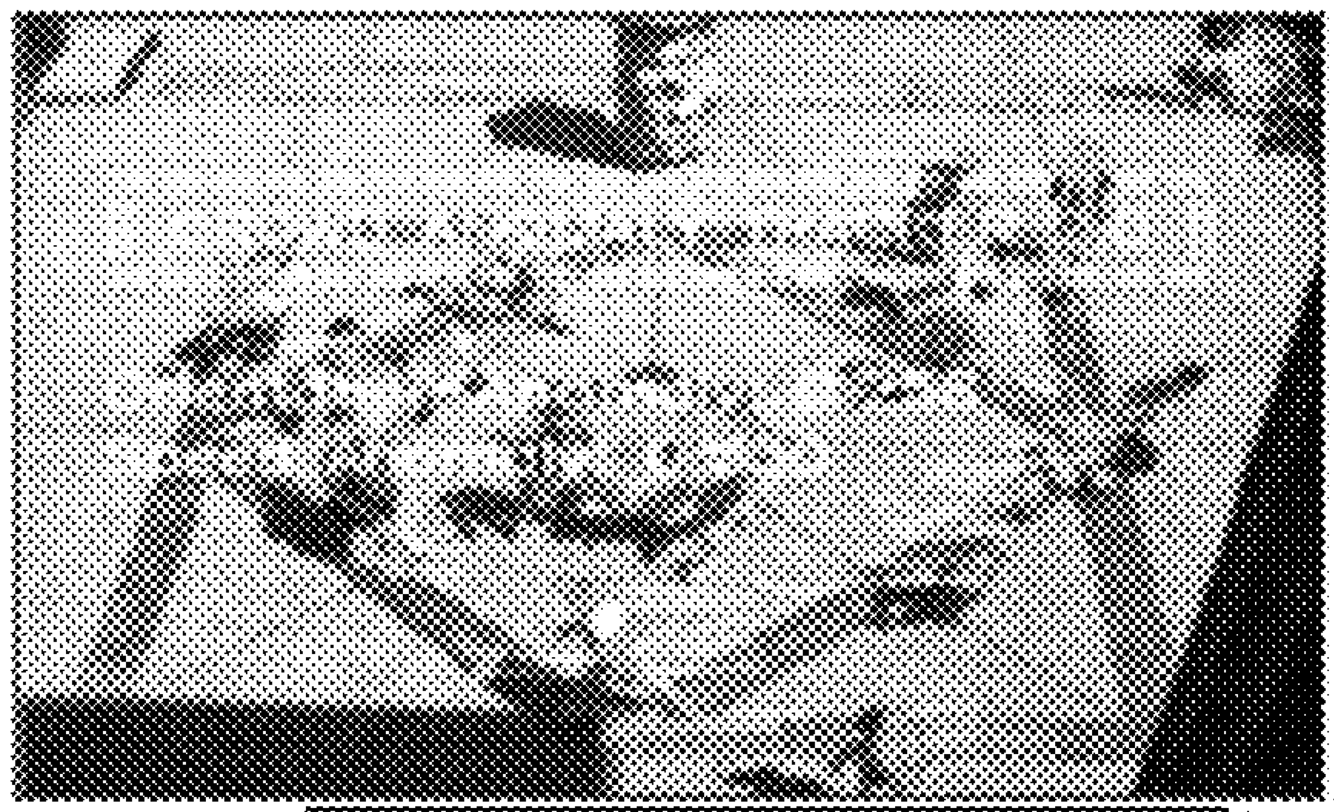
402(n)



1100

Metrics	Value
Speed	3 pix / frame
Direction	random
Count	12

402(n+1)



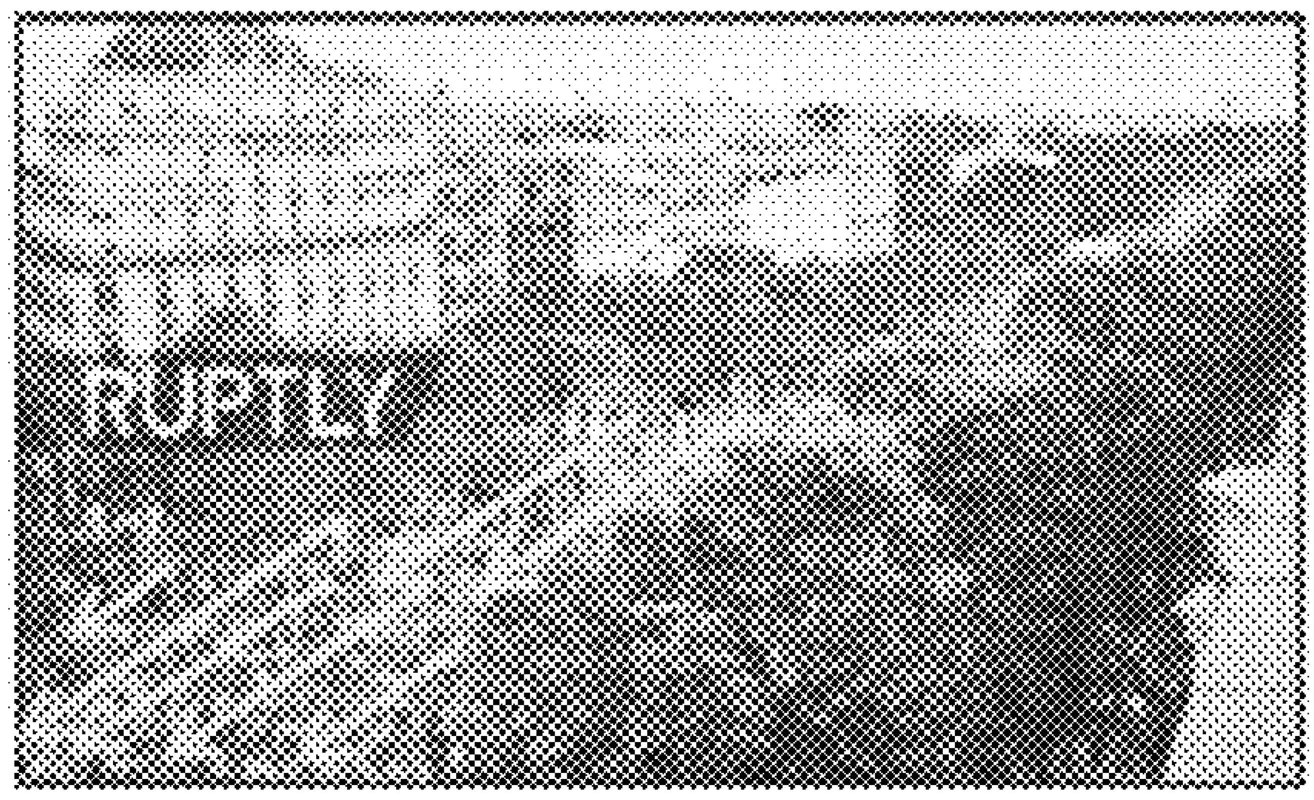
1102

Metrics	Value
Speed	7 pix / frame
Direction	scatter
Count	11

Crowd Panic Detection

FIG. 11A

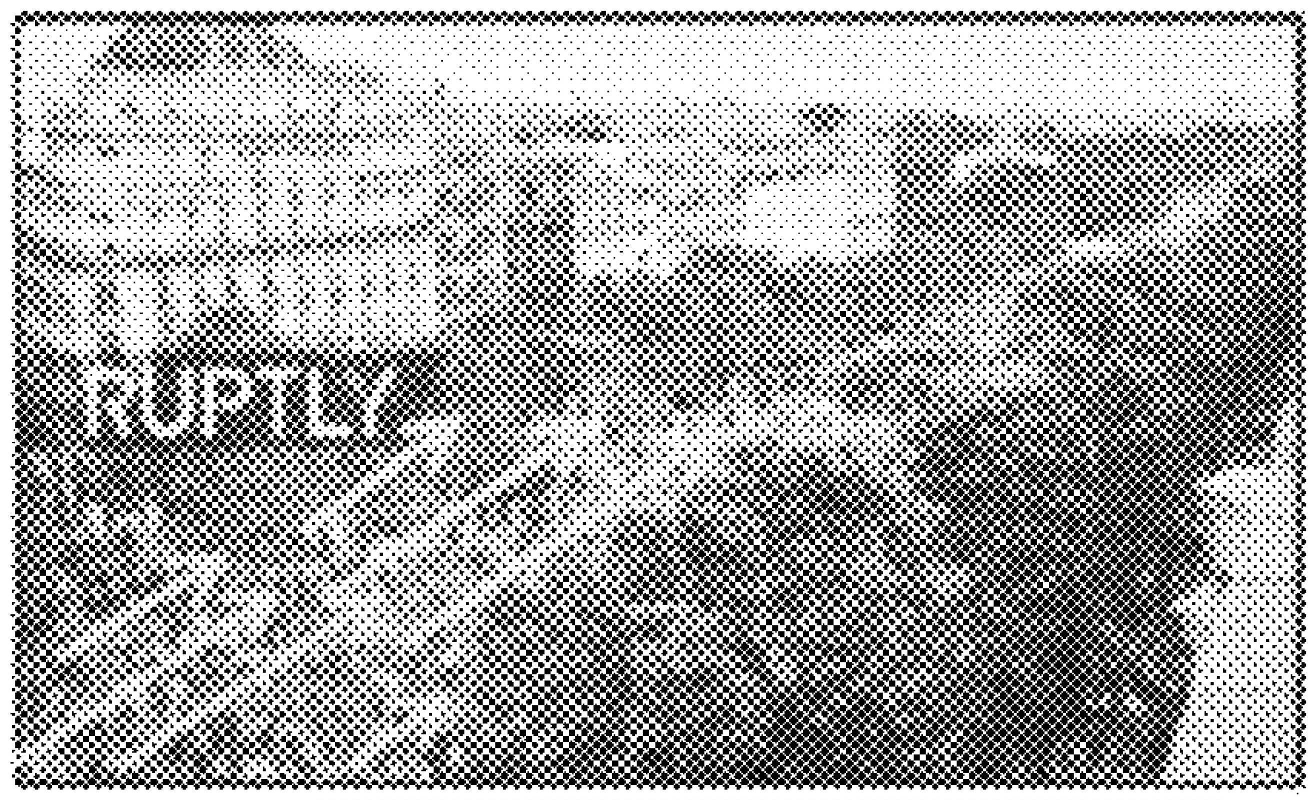
402(n)



1100

Metrics	Value
Speed	2 pix / frame
Direction	180°-225°
Count	164

402(n+1)



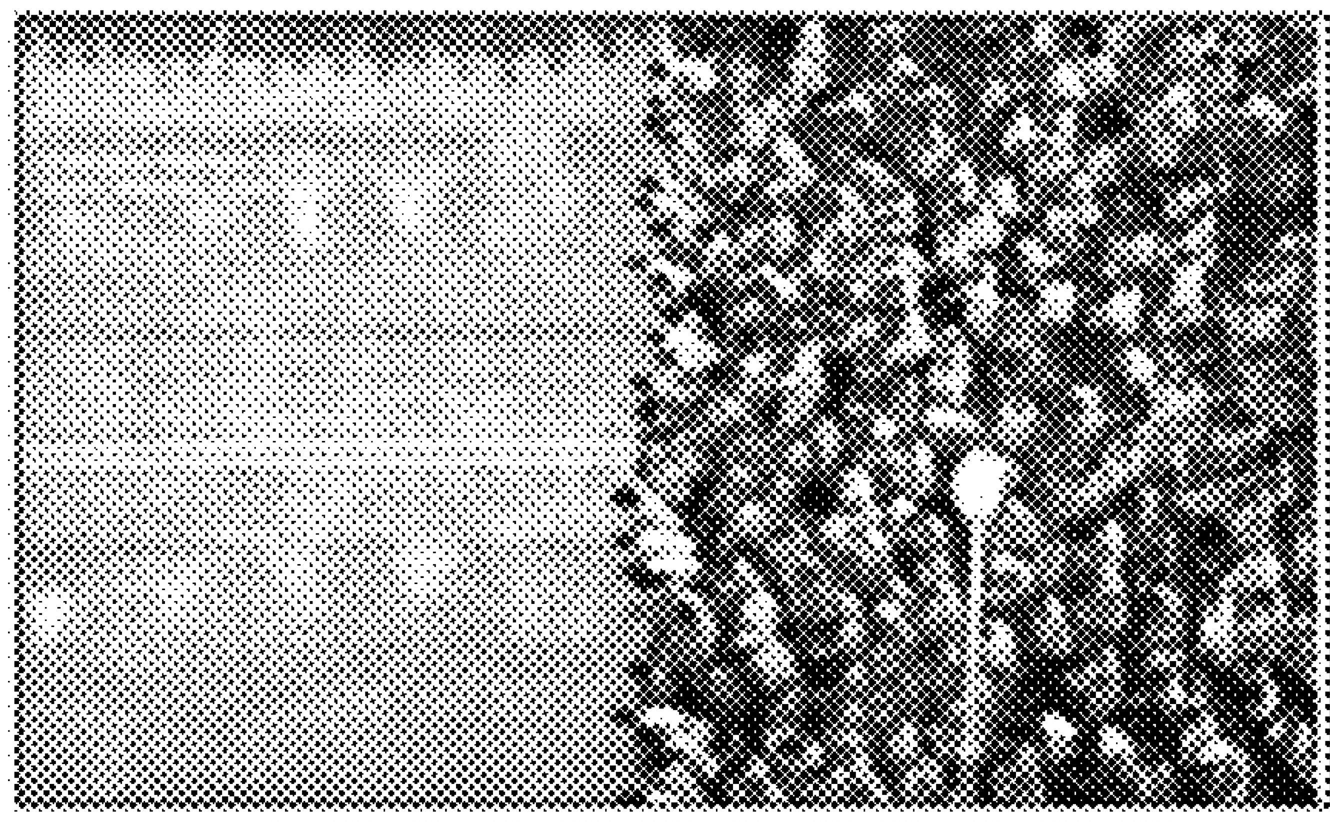
1102

Metrics	Value
Speed	2 pix / frame
Direction	15°-50°
Count	167

Crowd Moving in Wrong Direction Detection

FIG. 11B

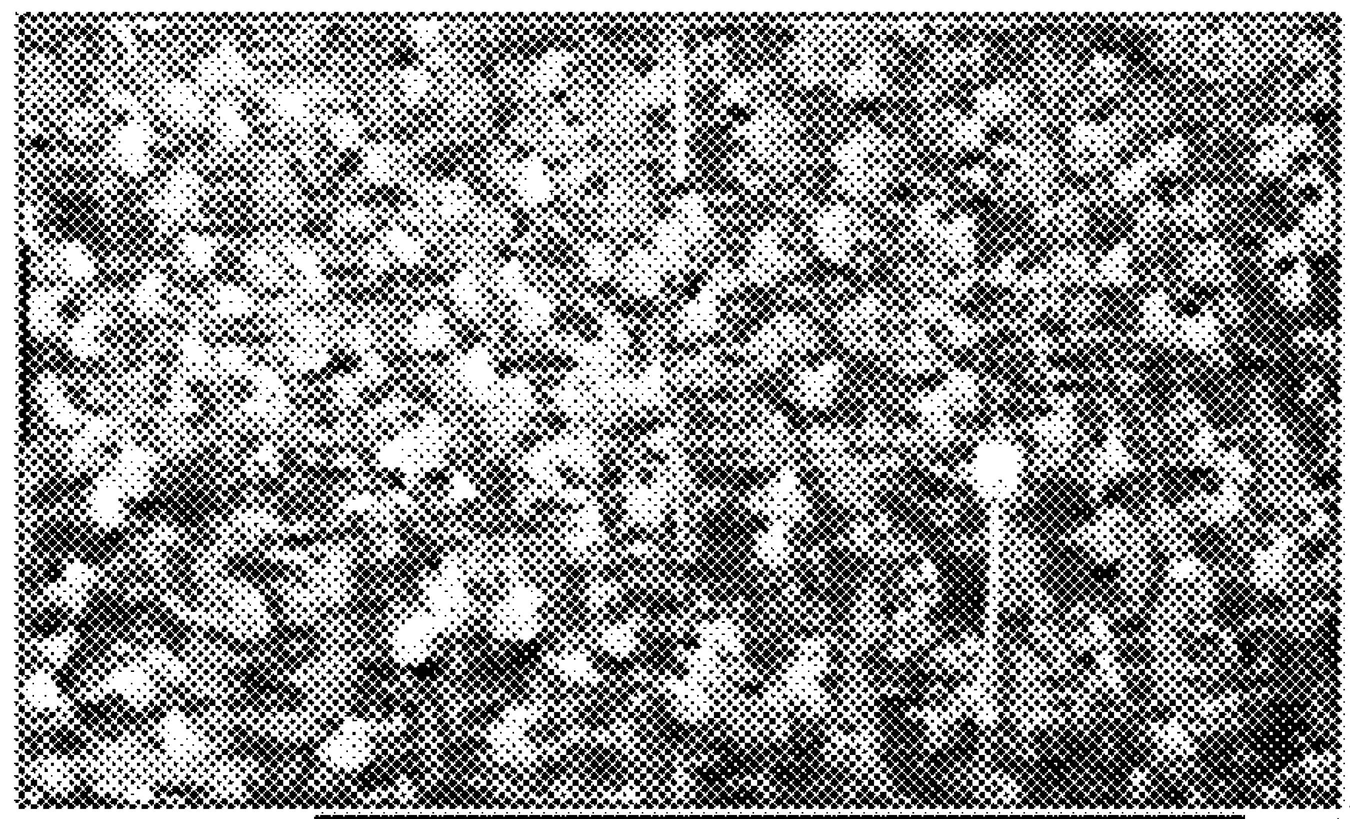
402(n)



1100

Metrics	Value
Speed	0 pix / frame
Direction	0°-10°
Count	138

402(n+1)



1102

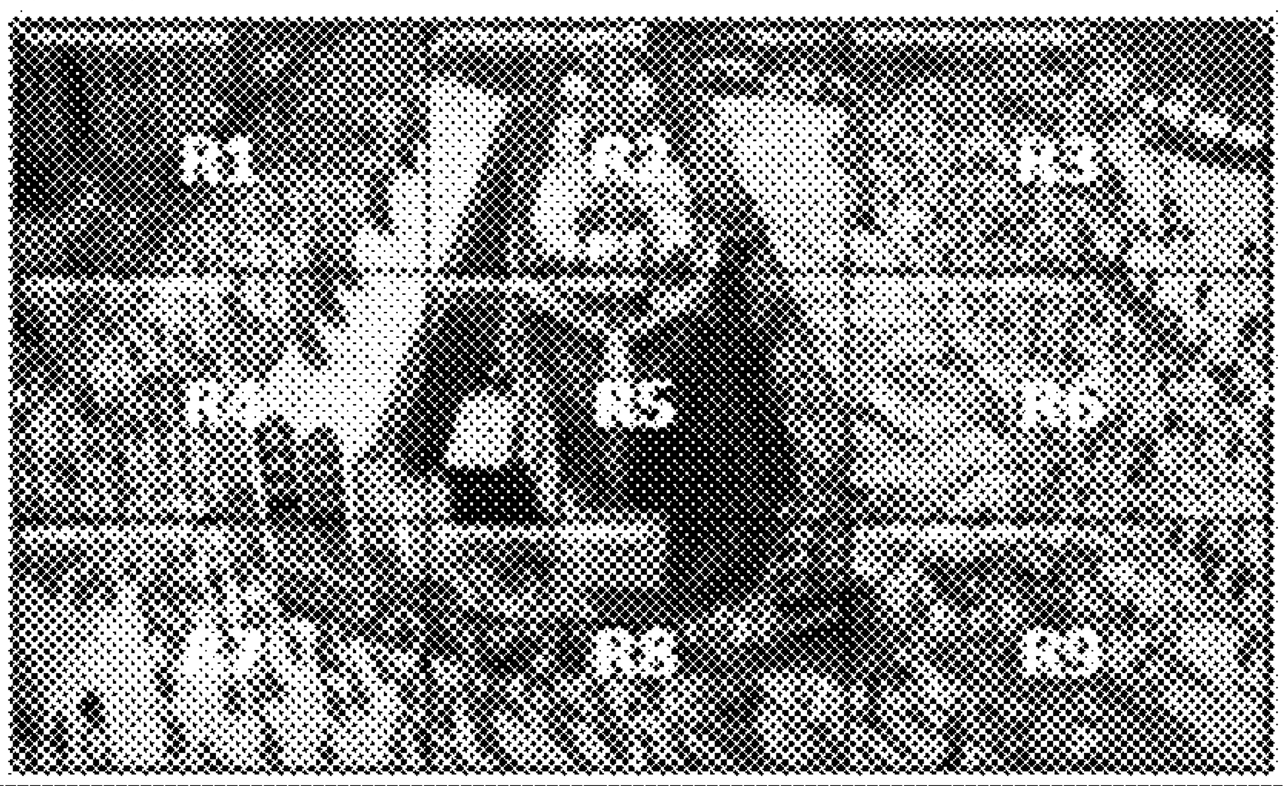
Metrics	Value
Speed	11 pix / frame
Direction	0°-10°
Count	277

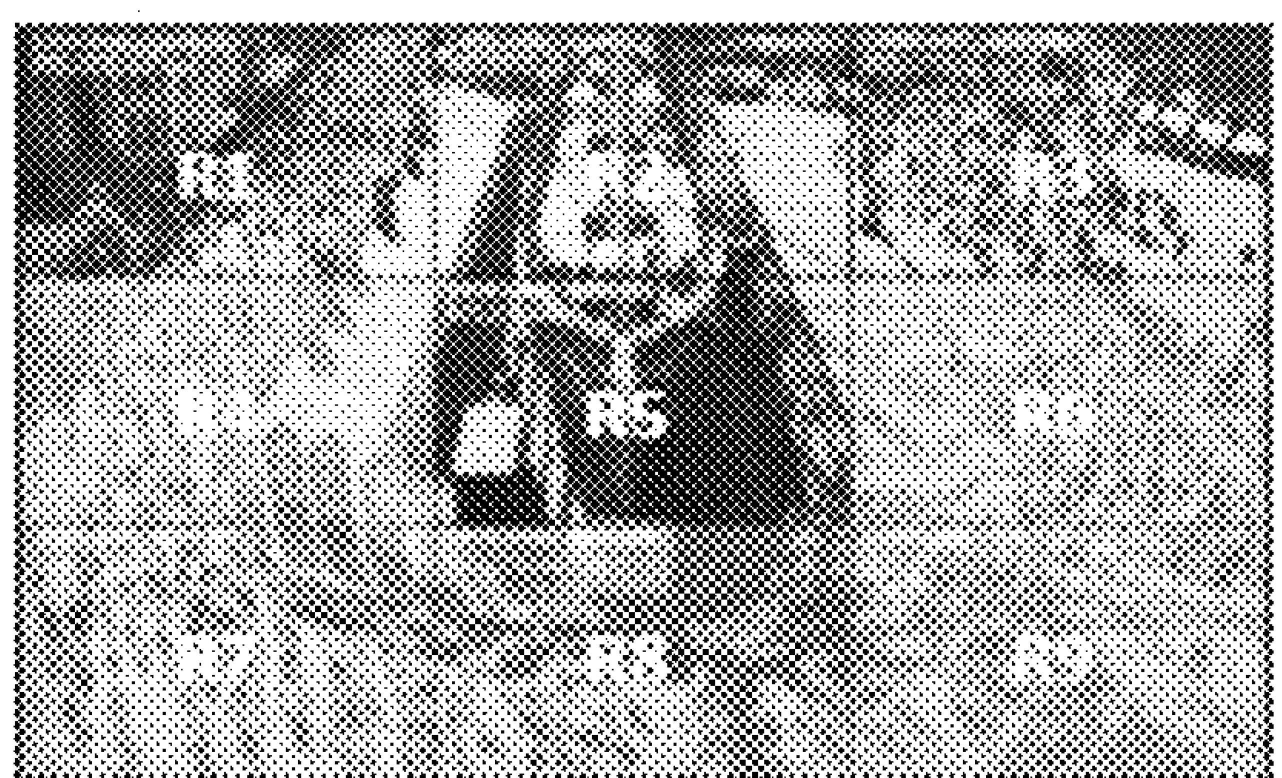
Crowd Stampede Detection

FIG. 11C

402(n)

402(n+1)





(pix/ frame)

Metrics	R1	R2	R3	R4	R5	R6	R7	R8	R9
Speed	1	0	1	2	0	2	4	5	4
Direction	↙	·	↖	↙	·	↖	↘	→	↗
Count	78	5	87	90	0	76	34	32	41

Metrics	R1	R2	R3	R4	R5	R6	R7	R8	R9
Speed	1	0	1	2	0	2	4	5	4
Direction	↙	·	↖	↗	·	↘	↖	←	↙
Count	78	5	82	90	1	72	34	31	41

1104

1106

Localized Unusual Motion Detection

FIG. 11D

METHODS AND SYSTEMS FOR CROWD MOTION SUMMARIZATION VIA TRACKLET BASED HUMAN LOCALIZATION

TECHNICAL FIELD

Example embodiments relate to video processing, for example crowd motion summarization of a video containing crowd motions.

BACKGROUND

Cameras can be used to capture videos of crowds. The videos can contain humans who are moving throughout the videos (some humans may be stationary). There is minimal work in the existing literature that combines information from crowd motion estimation and crowd counting. In rare cases where such a combination is considered, the main goal is to improve crowd count estimates by using motion information.

For example, in U.S. Pat. No. 9,576,199B2 to Zong et al., herein incorporated by reference, the inventors propose a method to compute the number and moving direction of pedestrians. They utilize Gaussian mixture modeling to remove static feature points and obtain a foreground pedestrian mask. Template maps around foreground feature points are tracked across frames to obtain a general trend of the crowd motion. A heuristic-based approach based on edge counting was used to count the number of pedestrians.

The background subtraction-based approach does not differentiate between crowds and other distractors within the scene that are moving such as cars, animals, and swaying trees. In addition, the formation of certain blobs by Zong et al. does not result in precise foreground/background binarization. As a result, the resulting crowd motion information and counting may not be representative of the true crowd statistics.

In Patent Application Publication No. US 2008/0118106 A1 to Kilambi et al., herein incorporated by reference, a crowd counting system is proposed that uses motion information. Kilambi et al. employ background subtraction to identify foreground moving regions; however, their method uses hand-crafted thresholds to differentiate between humans and other moving objects (e.g. vehicles). Kilambi et al. presented two additional modules within their system. The first module uses a Kalman filter to track individuals/groups of people, while the second module counts the number of people, whenever a foreground blob is sufficiently large. This count is achieved by projecting the foreground blob onto the ground plane and a second plane at the average height of a human. The blob is processed holistically with two assumptions to infer the count: 1) Humans move together with a fixed gap between adjacent members, and 2) The intersection of the projections onto the two planes is representative of the person count.

In addition to the limitations listed for Zong et al., the method of Kilambi et al. makes several assumptions to classify the blobs (crowds vs. other moving objects) and determine the counts within certain blobs. These assumptions are not realistic and result in numerous parameters that require optimization for each scene, making the approach infeasible and error-prone in real-world applications.

In Patzold et al.: Counting people in crowded environments by fusion of shape and motion information; 2010 7th IEEE International Conference on Advanced Video and Signal Based Surveillance, pages 157-164, IEEE, 2010, herein incorporated by reference, motion information is used for crowd counting in order to reduce the number of false positives. Specifically, Patzold et al. adopt a part-based detection technique that focuses only on detecting heads and shoulders, alleviating the occlusion issue to an extent. Patzold et al. state the advantage of this technique is that it relaxes the stringent assumption about the visibility of the entire human body. Their procedure fuses the spatial information of an adapted Histogram of Oriented Gradients (HOGs) based detector with temporal information by exploiting the distinctive motion characteristics of head-shoulder regions. Once the trajectories associated with a human are validated, they are used to identify the number of individuals in a scene.

Patzold et al. presumes that the head-shoulder regions are always visible, which will not be true in densely populated scenes nor for certain camera viewpoints. The head-shoulder requirement restricts the approach to a narrow range of deployment settings. Further, the motion signatures of the head-shoulder regions are localized using a hand-crafted binary template, which implicitly assumes the head/shoulder size and camera viewpoint. If the camera position were to change, the current template would be ineffective. This scene-specific template makes the approach unscalable and inflexible.

In Hashemzadeh et al.: Counting moving people in crowds using motion statistics of feature-points; Multimedia Tools and Applications, 72(1):453-487, 2014, herein incorporated by reference, the authors propose a trajectory-clustering-based technique for crowd counting. The technique detects independent motions by clustering interest points on people tracked over time. Hand-crafted features are extracted from each cluster and provided to a classifier to estimate the number of moving people in that cluster.

Hashemzadeh et al. can suffer from occlusion between individuals and other scene objects because it depends heavily on the effectiveness of the tracking technique. Furthermore, it is challenging to cluster local features for huge and dense crowds with heavy occlusions and random fluctuations. Another drawback is that the hand-crafted features used to determine the number of pedestrians corresponding to a point cluster are predicated using a number of assumptions (e.g., linear relationship between interest points and person counts, boundary identification). Finally, similar to most prior art, this work assumes that humans are the only moving objects within the scene. Other moving objects (e.g., vehicles, animals, etc.) cannot be detected or removed, limiting this systems effectiveness in the real-world.

In Ryan et al.: Crowd counting using group tracking and local features; 2010 7th IEEE International Conference on Advanced Video and Signal Based Surveillance, pages 218-224, IEEE, 2010, herein incorporated by reference, motion cues and tracking are used to create a person counting system. Similar to other disclosures as noted above, Ryan et al. group people using blobs in an extracted foreground image. Ryan et al. provides the set of hand-crafted local features that are extracted from these blobs (e.g., area, perimeter, edge-angle histograms, etc.). These features are fed into a least-squares linear model to regress the number of people. Inter-frame tracking is used to improve the robustness of the count estimates in a rule-based fashion, identifying events such as the splitting or merging of blobs.

In Ryan et al., the representational power of these extracted features from blobs (e.g., area, perimeter) heavily relies upon the foreground segmentation results, which are known to be notoriously noisy in practice. Even assuming precise foreground segmentation, the accuracy of the detection algorithm depends on the selection of features. Hand-crafted features based on foreground blob shape and size are unlikely to generalize well to new environments, as they are highly dependent on the camera viewpoint and angle.

Another example where the motion information is used to improve counting is given in Liang et al.: Counting crowd flow based on feature points; Neurocomputing, 133:377-384, 2014, herein incorporated by reference. Liang et al. applied a three-frame difference algorithm to extract a binary mask containing movement only. The region of the binary mask is used to extract SURF (Speeded Up Robust Features) features which are clustered using an improved version of DBSCAN (Density-Based Spatial Clustering of Applications with Noise). Eigenvector-based features are extracted from the clusters and provided to a support vector regressor to attain person counts as well as the orientation of motion.

Although Liang et al. propose a technique to reduce the effects of perspective distortion, the technique may not work generally because the technique presumes that the bottom points of the cluster lie on the ground plane. Foreground detection imperfections or occlusions can violate this assumption. In addition, the assumption of motion coherency of a crowd may not always be valid due to limb articulation. Finally, like most existing disclosures, Liang et al. presumes the only moving objects within the scene are humans.

In Sidla et al.: Pedestrian detection and tracking for counting applications in crowded situations; International Conference on Advanced Video and Signal-Based Surveillance (AVSS), pages 70-75, 2006, herein incorporated by reference, a pedestrian detection and tracking system is proposed that enables the counting of persons in densely crowded scenes by combining motion estimation, texture analysis and shape matching. First, the system computes a region of interest poll containing every foreground shape using foreground segmentation. Second, contour-based searching methods are applied (e.g. Canny Edge detector) followed by Active Shape Model (ASM) to detect the shape of humans with the goal of reducing the search space by limiting unnecessary edges/areas from the Region of Interest (ROI) poll. Eventually, after filtering out the ROI poll, Sidla et al. applies KLT (Kanade-Lucas-Tomasi) algorithm to obtain trajectories to track the detected shapes. In addition, Sidla et al. apply trajectory clustering to obtain the people count.

Sidla et al. is able to differentiate pedestrian movement from other objects by shape matching (head and shoulders); however, in crowded scenes (e.g. playgrounds, protests, shopping malls) due to perspective distortion, severe occlusion might occur, making this approach less practical. Moreover, this model suffers from the common restrictions of foreground segmentation (e.g., color camouflage, moving backgrounds etc.).

In Chinese Patent Application Publication CN107292908A to Liu et al. entitled Pedestrian Tracting Method Based On KLT Feature Point Tracking Algorithms, herein incorporated by reference, the inventors propose a person tracking method that combines detection and the KLT algorithm. Liu et al. disclose a feature filtering process, which localizes the people in the image for tracking. The inventors use a Histogram of Oriented Gradients (HoG) feature selection method. With the extracted features, Liu et al. train a classifier that is able to detect humans. KLT feature tracking is applied within the areas corresponding to the humans, thus performing target tracking.

In Liu et al., the computation cost for HoG and SVM are very high. In real-time environments, this algorithm might suffer from inference complexity. Moreover, HoG are traditional, hand-crafted features. Recent advances in computer vision have universally demonstrated that visual features learned using deep learning methods significant outperform hand-crafted features. A further limitation of this work is that detection-based methods tend to break down in complicated scenes where the size of the visible persons is small and there is significant inter-person occlusion. In such scenarios, regression based approaches (e.g., crowd counting networks) tend to provide more accurate person localization.

It is desirable to provide a crowd motion summarization method that can automatically and efficiently summarize crowd movements from a video.

It is desirable to use crowd density estimates to extract more accurate crowd movements from a video.

It is desirable to provide a crowd motion summarization method that can generate crowd motion data that combines crowd motion estimation and crowd counting.

It is desirable to provide a crowd motion summarization method that is applicable to a wide range of applications with minimal reliance on hand-crafted features.

SUMMARY

Example embodiments provide a crowd motion summarization method, device and system, to generate crowd motion data from a video. The video frame can contain humans, non-human objects, and background. For example, the crowd motion summarization method, device and system can be used to automatically and efficiently count crowds (humans), crowd speeds and crowd orientations in the video.

According to a first aspect, the method is for crowd counting and crowd motion summarization of a video containing video frames. A feature tracking module receives each video frame and detects features (feature points) from the video frame. A crowd occupancy detection module receives the video frame and detects human location from the video frame, and generates a binary crowd occupancy map having human pixel positions indicate the human location versus non-human location. The crowd occupancy detection module generates a total human count of the humans detected in the video frame. The feature tracking module generates feature tracking information for only those features contained in the human pixel positions which indicate the human location. A feature-crowd matching module generates, from the feature tracking information of one or more of the features and the total human count: crowd motion data. A data visualization module generates, using the crowd motion data: visualization data. The method outputs the visualization motion data.

A technical effect of the crowd motion summarization method of example embodiments is that the method can be automatically and efficiently summarize crowd movements from a video.

Another technical effect of the crowd motion summarization method is that the binary crowd occupancy map provides a filter to better delineate image regions corresponding to a crowd, yielding more robust, accurate motion estimates.

Another technical effect of the crowd motion summarization method is that the binary crowd occupancy map can be generated using the video frame without regard to previous video frames, and therefore does not require complex labelling or human tracking algorithms.

Another technical effect of the crowd motion summarization method is that other distracting moving objects (e.g., cars, motorcycles, swaying trees, flying birds) are removed via the binary crowd occupancy map. The crowd motion summarization method produces a more pure measure of crowd motion, is robust to illumination changes, and requires less or no computation on the non-human pixel positions of the binary crowd occupancy map.

Another technical effect is that the crowd motion summarization method uses crowd density estimates to extract more accurate crowd motion from the video frame.

Another technical effect is that the crowd motion data is generated for each frame by comparing to the previous frame, which does not require entire video files.

In an example of the first aspect, the crowd motion data includes: i) a human speed count of human speed, ii) a human orientation count of human orientation, and iii) a time of the video frame.

A technical effect of the crowd motion summarization method of example embodiments is that the method can generate, from the video, the crowd motion data that combines crowd motion estimation and crowd counting.

In an example of the first aspect, the crowd motion summarization method includes generating the histogram of motion summaries in near real-time, as-needed, as soon as the crowd motion data is generated from each subsequent video frame.

A technical effect is that the crowd motion data is generated for each frame by comparing to the previous frame, which does not require entire video files in order to generate real-time crowd motion data.

In an example of the first aspect, the crowd motion summarization method includes generating, using the crowd visualization module, a histogram of motion summaries, as follows: first histogram of human speed, time, human speed count; and second histogram of human orientation, time, human orientation count.

A technical effect of the crowd motion summarization method is that the histogram of motion summaries combines crowd motion and person counts to create a rich descriptor of crowds in videos.

In an example of the first aspect, the crowd motion summarization method includes receiving a video frame; generating, using a crowd occupancy detection module and the video frame: a binary crowd occupancy map of the video frame having human pixel positions which indicate human location versus non-human location, and a total human count of humans detected in the video frame; generating, using a feature tracking module and the video frame: a feature map including feature location of features detected in the video frame; generating, using the feature tracking module, the feature map, the binary crowd occupancy map, the video frame, a previous video frame, and previous feature location of previous features detected from the previous video frame: feature tracking information for only each feature in the human pixel positions for the video frame, including: i) the feature location, ii) feature speed, iii) feature orientation, and iv) total feature count; and generating, using a feature-crowd matching module, the feature tracking information, and the total human count: crowd motion data including: i) a human speed count of at least one human speed, ii) a human orientation count of at least one human orientation.

In an example embodiment of any of the above, the crowd motion data further includes: iii) time of the video frame, the method further comprising generating, using a data visualization module and the crowd motion data: visualization data of the crowd motion data.

In an example embodiment of any of the above, the method further includes generating, using the data visualization module: the visualization data including at least one table which includes the human speed count and the human orientation count.

In an example embodiment of any of the above, the method further includes generating, using the data visualization module: the visualization data including at least one table which includes: i) the human speed count, ii) the human orientation count, and iii) the time of the video frame.

In an example embodiment of any of the above, the method further includes generating the visualization data for at least one other video frame, wherein the at least one table further includes: a first histogram of the human speed count, the human speed, and the time, and a second histogram of the human orientation count, the human orientation, and the time.

In an example embodiment of any of the above, the method further includes generating, using the data visualization module and the video frame: a first overlay of the video frame with the crowd motion data overlaid on the video frame.

In an example embodiment of any of the above, the method further includes generating, using the data visualization module and the previous video frame: a second overlay of the previous video frame with previous crowd motion data overlaid on the previous video frame; and generating the crowd motion data to display the first overlay and the second overlay on a same display screen.

In an example embodiment of any of the above, the generating the crowd motion data is performed in near real-time when the video frame is received.

In an example embodiment of any of the above, the generating the binary crowd occupancy map using the crowd occupancy detection module includes: generating, using a crowd density estimating module and the video frame: a crowd density map which includes a probability of the human location; generating, using a binary threshold module and the crowd density map: a threshold binary crowd occupancy map of the crowd density map for the probability that exceeds a threshold, the threshold binary crowd occupancy map having the human pixel positions which indicate the human location versus the non-human location; and generating, using a morphological transformation module and the threshold binary crowd occupancy map: the binary crowd occupancy map from the threshold binary crowd occupancy map which accounts for morphological human features.

In an example embodiment of any of the above, the morphological transformation module includes a dilation module configured to dilate the human pixel positions which indicate the human location.

In an example embodiment of any of the above, the features are Kanade-Lucas-Tomasi (KLT) features, wherein the feature tracking information includes KLT feature tracking information, wherein the feature locations are KLT feature locations, wherein the generating the feature tracking information includes: generating, using a KLT feature extraction module and the video frame: a KLT feature map of KLT feature location of the KLT features detected in the video frame; generating, by element-wise multiplying of the KLT feature map with the binary crowd occupancy map: a filtered KLT feature map with only the KLT feature locations in the human pixel positions for the video frame; generating, using a KLT feature tracking module: a respective feature tracklet between the KLT feature location of each KLT feature and a previous KLT feature location detected from the previous video frame; and generating, using a speed and orientation estimator module and the respective feature tracklet: the feature tracking information for each KLT feature, including: KLT feature speed, and KLT feature orientation.

In an example embodiment of any of the above, the features are KLT features, and wherein the feature tracking information includes KLT feature tracking information.

In an example embodiment of any of the above, the generating using the feature-crowd matching module includes estimating a number of the features per human.

In an example embodiment of any of the above, the feature orientation for an i^{th} feature is calculated as:

$$\theta^i = \arctan\frac{(y_n^i - y_{n-1}^i)}{(x_n^i - x_{n-1}^i)};$$

and

wherein the feature speed for the i^{th} feature is calculated as:

$$M^i = \sqrt{(x_n^i - x_{n-1}^i)^2 + (y_n^i - y_{n-1}^i)^2},$$

wherein (x, y) are Cartesian co-ordinates of the feature location for the i^{th} feature, n is the video frame, and n−1 is the previous video frame.

In an example embodiment of any of the above, the method further includes: receiving the previous video frame; and generating, using the feature tracking module, for each previous feature detected in the previous video frame: the previous feature location.

In an example embodiment of any of the above, the method further includes: generating, using the crowd occupancy detection module and the previous video frame: a previous binary crowd occupancy map of the previous video frame having the human pixel positions which indicate the human location versus the non-human location; and wherein the generating the previous feature location is performed on only each feature in the human pixel positions of the previous binary crowd occupancy map for the previous video frame.

In an example embodiment of any of the above, the generating the binary crowd occupancy map uses the video frame without using any previous video frame or any previous binary crowd occupancy map.

In an example embodiment of any of the above, the crowd occupancy detection module includes a crowd occupancy detection model.

In an example embodiment of any of the above, the feature tracking module includes a feature tracking model.

According to a second aspect, a crowd motion summarization system is provided, where the crowd motion summarization system includes modules configured to perform the method in the first aspect.

In an example embodiment of the second aspect, the crowd motion summarization system includes the following modules: the feature tracking module, the crowd occupancy detection module, the feature-crowd matching module, and the data visualization module.

In an example embodiment of the second aspect, the modules each include a model. In some examples, each model is a trained model.

According to a third aspect, a crowd motion summarization apparatus is provided, where the crowd motion summarization apparatus includes: a memory, configured to store a program; at least one processor, configured to execute the program stored in the memory, and when the program stored in the memory is executed, the at least one processor is configured to perform the method in the first aspect. In an example embodiment of the third aspect, the crowd motion summarization apparatus is a user equipment.

According to a fourth aspect, a computer readable medium is provided, where the computer readable medium stores program code executed by the crowd motion summarization apparatus, and the program code performs the method in the first aspect when executed by at least one processor of the crowd motion summarization apparatus.

According to a fifth aspect, a computer program product including instructions is provided. When the computer program product is run on a computer, the crowd motion summarization apparatus performs the method in the first aspect.

According to a sixth aspect, a computer chip is provided, where the computer chip includes a processor and a data interface, and the processor reads, by using the data interface, instructions stored in a memory, to perform the method in the first aspect.

Optionally, in an implementation, the computer chip may further include the memory. The memory stores the instructions, and the processor is configured to execute the instructions stored in the memory. When the instructions are executed, the processor is configured to perform the method in the first aspect.

BRIEF DESCRIPTION OF THE DRAWINGS

Reference will now be made, by way of example, to the accompanying drawings which show example embodiments, and in which:

FIG. **1** is a schematic structural diagram of a system architecture of a crowd motion summarization system, in accordance with an example embodiment;

FIG. **2** is a schematic diagram of a hardware structure of a chip according to an example embodiment of the crowd motion summarization system;

FIG. **3** is a pictorial representation of the crowd motion summarization system, in accordance with an example embodiment;

FIG. **4** is an example crowd motion summarization method performed by the crowd motion summarization system, in accordance with an example embodiment;

FIG. **5** is a detail flow diagram of crowd occupancy detection performed by the crowd motion summarization system, in accordance with an example embodiment;

FIG. **6** is a detail flow diagram of feature tracking performed by the crowd motion summarization system;

FIG. **7** is a detail pictorial representation of data generated by each module of the crowd motion summarization system, in accordance with an example embodiment;

FIG. **8** is a schematic diagram of a data visualization module of the crowd motion summarization system, in accordance with an example embodiment;

FIG. **9** illustrates an example histogram of motion summaries generated by the data visualization module;

FIG. **10** illustrates an example overlay of a video frame generated by the data visualization module;

FIG. **11**A illustrates an example of two sequential video frames overlaid with crowd motion data representing crowd panic detection, generated by the data visualization module;

FIG. **11**B illustrates an example of two sequential video frames overlaid with crowd motion data representing crowd moving in wrong direction detection, generated by the data visualization module;

FIG. **11**C illustrates an example of two sequential video frames overlaid with crowd motion data representing crowd stampede detection, generated by the data visualization module; and

FIG. **11**D illustrates an example of two sequential video frames overlaid with crowd motion data representing localized unusual crowd motion detection, generated by the data visualization module.

Similar reference numerals may have been used in different figures to denote similar components.

DETAILED DESCRIPTION

The following describes technical solutions of example embodiments with reference to accompanying drawings.

The terms person and human are used interchangeably herein.

A crowd includes a plurality of humans, which can be some, hundreds, or at least thousands of humans. Examples of the crowd motion summarization system and the crowd motion summarization method in accordance with example embodiments can be used to detect and summarize movement of as few as one human.

In some examples, a video can be considered a sequence of images (generally referred to as video frames).

In some examples, the location or position of an object in a video frame is represented by: a Cartesian co-ordinate such as (x, y) or (x, y, z) (i.e. a pixel), a plurality of pixels, a bounding box (which can be represented by two diagonal pixels), a polygon box, or a 2-Dimensional map (having one or more color channels) in which one or more pixel positions have a particular pixel value (e.g. a mask, outline, or edges of the object).

An example embodiment is an execution device or a user equipment configured to execute a crowd motion summarization method which generates crowd motion data from a video. The video contains video frames which contain humans (i.e., a crowd) that move throughout the video. For example, the crowd motion summarization method can be used to count, over a number of video frames, the total number of humans, count humans that are moving at a given speed, and count humans that are moving at a given orientation (angular direction).

The crowd motion summarization method automatically processes each video frame containing humans, and is able to generate crowd motion data from the video frame by comparing to a previous video frame.

The crowd motion summarization method provided in example embodiments can be applied to a first example scenario in which a video frame of a video contains humans having crowd motion that may be summarized. The video frame is received by a camera, for example by using an on-board camera of a user equipment, or another camera, to capture a video frame. The method processes the video frame and detects features (feature points) from the video frame. The method processes the video frame and detects humans from the video frame, and generates a binary crowd occupancy map having human pixel positions indicate the human location versus non-human location. The method generates a total human count. The method generates feature tracking information for only those features contained in the human pixel positions which indicate the human location. The method generates, using the feature tracking information and the total human count: crowd motion data. The method outputs the crowd motion data.

Therefore, a technical effect of the crowd motion summarization method is that the method can be automatically and efficiently summarize crowd movements from a video.

Another technical effect of the crowd motion summarization method is that the binary crowd occupancy map provides a filter to better delineate image regions corresponding to a crowd, yielding more robust, accurate motion estimates.

Another technical effect of the crowd motion summarization method is that the binary crowd occupancy map can be generated using the subject video frame only without regard to previous video frames, and therefore does not require complex labelling or human tracking algorithms.

Another technical effect of the crowd motion summarization method is that other distracting moving objects (e.g., cars, motorcycles, swaying trees, flying birds) are removed via the binary crowd occupancy map. The crowd motion summarization method produces a more pure measure of crowd motion, is robust to illumination changes, and requires less or no computation on the non-human pixel positions of the binary crowd occupancy map.

Another technical effect is that the crowd motion summarization method uses crowd density estimates to extract more accurate crowd motion from the video frame.

Another technical effect is that the crowd motion data is generated for each frame by comparing to the previous frame, which does not require entire video files.

The crowd motion summarization method provided in example embodiments can be applied to a second example scenario in which the user camera has an onboard camera which captures video frames. The user equipment performs the crowd motion summarization method and receives the video frame and generates crowd motion data from the video frame. The user equipment outputs the crowd motion data to a display screen of the user equipment.

In another example of the second example scenario, the user equipment generates the crowd motion data in near real-time, as-needed, as soon as the video frames are captured by the onboard camera.

FIG. **1** illustrates a system architecture of a crowd motion summarization system **100** in accordance with an example embodiment. One or more processing unit(s) **111** can include a host CPU and other processing units (a Neural Processing Unit (NPU), a tensor processing unit (TPU), a graphics processing unit (GPU), or the like). The processing unit(s) **111** execute modules **101**, which include a feature tracking module **101**A, a crowd occupancy detection module **101**B, a feature-crowd matching module **101**C, and a data visualization module **101**D.

The modules **101** can be used to implement aspects of the crowd motion summarization method (FIG. **4**) according to an example embodiment. The input to the modules **101** can be a video frame **402** of a video which contains one or more humans. The video frame **402** can be received from a camera **142** or from a user equipment **140**.

In an example, the modules **101** each include a trained model. By way of example, the feature tracking module **101**A can include a feature tracking model, the crowd occupancy detection module **101**B can include a crowd occupancy detection model, the feature-crowd matching module **101**C can include a feature-crowd matching model, and the data visualization module **101**D can include a data visualization model.

In an example, the feature tracking module **101**A is configured to detect features in the video frame **402**. In an example, the features are feature points (also known as feature edge points, KLT corners or Harris corners) of visual features of particular edges detected from the video frame **402**. The feature tracking module **101**A generates, using the video frame **402**: a feature map including feature location of each feature (edge point) detected in the video frame **402**. For example, the feature tracking module **101**A generates a feature map which indicates each feature location of each feature as a pixel.

In an example, the crowd occupancy detection module **101**B is configured to generate, using the video frame **402**: human localization information of humans detected in the video frame **402**, including: a binary crowd occupancy map of the video frame **402**, and a total human count of the humans detected in the video frame. The binary crowd occupancy map has human pixel positions which indicate the human location versus non-human location.

In an example, the crowd occupancy detection module **101**B can include a crowd occupancy detection model. An example trained crowd occupancy detection model of the crowd occupancy detection module **101**B is illustrated in FIG. **5**, and is described in greater detail herein below. The crowd occupancy detection module **101**B can include a deep neural network (DNN).

The feature tracking module **101**A is also configured to generate, using the filtered feature map, the binary crowd occupancy map, the video frame, a previous video frame and a previous filtered feature map of the previous video frame: feature tracking information for each feature in the human pixel positions for the video frame **402**, including: i) feature location, ii) feature speed, iii) feature orientation, and iv) total feature count.

In an example, the feature tracking module **101**A can include a feature tracking model. An example trained feature tracking model of the feature tracking module **101**A is illustrated in FIG. **6**, and is described in greater detail herein below. The feature tracking module **101**A can include a DNN. In an example, the feature tracking module **101**A can include a Kanade-Lucas-Tomasi (KLT) feature tracking model obtained from a library.

In an example, the feature-crowd matching module **101**C is configured to generate, using the feature tracking information and the total human count: the crowd motion data **404**. The crowd motion data **404** includes: i) human speed count, ii) human orientation count, iii) total human count, and iv) time.

In an example, the feature-crowd matching module **101**C includes a set of rules for matching features with human localization information detected in the video frame **402**. For example, the feature-crowd matching module **101**C divides the total human count by the total feature count, arriving at an average number of features per human in the video frame **402**. The feature-crowd matching module **101**C includes rules as to how to generate (infer) the crowd motion data **404** from the average number of features per human and the feature tracking information. The inference can be made using statistical averages from the average number of features per human.

In an example, the feature-crowd matching module **101**C can include a feature-crowd matching model. The feature-crowd matching model infers, from the total count and the feature tracking information: the total human speed count and the total human orientation. An example trained feature-crowd matching model of the feature-crowd matching module **101**C is illustrated in FIG. **4**, and is described in greater detail herein below.

In an example, the data visualization module **101**D is configured to generate, from the crowd motion data **404** and the video frame **402**: visualization data **420**. In an example, the visualization data **420** and the crowd motion data **404** can provide a rich descriptor for crowds in the video frame **402**.

An example of the visualization data **420** generated by the feature-crowd matching module **101**C is illustrated in FIGS. **9**, **10**, **11**A, **11**B, **11**C, and **11**D and is described in greater detail herein below.

In some examples, the data visualization module **101**D is configured to generate an overlay of the crowd motion data **404** that is overlaid on the video frame **402**. In some examples, the data visualization module **101**D is configured to generate histograms, tables, summaries, charts, graphs, etc. In some examples, the data visualization module **101**D is configured to detect an event from the crowd motion data **404**, and generates an event indication as an output that indicates occurrence of the event.

In an example, the data visualization module **101**D can include a data visualization model. For example, the data visualization model can be trained with crowd motion data **404** and the resultant visualization data **420** that was desired for that particular crowd motion data **404**. The particular slot intervals of the visualization data **420**, such as human orientation and human speed, can be generated by the data visualization model **420**.

In FIG. **1**, the execution device **110** includes a network I/O interface **112** for communicating with a camera **142** using a communication protocol to receive the video frame **402** from the camera **142** and to transmit crowd motion data **404** to the user equipment **140**. In an example, the camera **142** is an Internet Protocol (IP) camera that is configured to send video over a network or the Internet. A user may input data to the user equipment **140** which is then communicated to the I/O interface **112** using wired or wireless communication. In another example, the execution device **110** is part of the user equipment **140**, and the user may input data over the I/O interface **112** to the execution device **110**. In another example, the camera **142** is part of the execution device **110**, and camera **142** transmits data over the I/O interface **112** to the execution device **110**. In another example, the user equipment **140** includes the camera **142**. In another example, second user equipment (not shown here) includes the camera **142**.

The camera **142** can capture and transmit real-time video (e.g., as streaming video), or can capture and transmit video in batches, or can capture and transmit time-elapsed video. In some examples, the camera can capture a video for a particular time period and store the video in a memory. In an example embodiment, the input data may include: a video frame **402** generated (captured) by the camera **142**. The camera **142** can also generate time data (time) associated with each video frame **402**, such as a sequential video frame number, or a clock time. The time can be stored as metadata or within the video or the video frame **402**. The camera **142** can be mounted to a stationary object, such as a building or pole. The camera **142** can be part of a mobile device, such as a dashboard camera of a vehicle, body camera, smart glasses, aerial camera (e.g. drone), handheld communication device, etc. The **142** camera can be manually or digitally controlled to captured desired orientations, such as Pan, Tilt and Zoom (PTZ).

In example embodiments, the video frame **402** is retrieved from the execution device **110** itself, the user equipment **140** itself, a different user equipment device, a cloud server, an Internet Protocol (IP) address, an externally accessed user account, an externally accessed social media account, or a video frame from the World Wide Web, etc.

In an optional example, a preprocessing module **114** is configured to perform preprocessing based on the input data (for example, the video frame **402**) received via the I/O interface **112** from the camera **142** or the user equipment **140**. In a related processing process in which the preprocessing module **114** performs preprocessing on the input data or the processing unit(s) **111** in the execution device **110** performs computation, the execution device **110** may invoke data, code, or the like from a data storage system **150**, to perform corresponding processing, or may store, in a data storage system **150**, data, an instruction, or the like obtained through corresponding processing. An example of preprocessing performed by the preprocessing module **114** is converting a color version of the video frame **402** to a grayscale version. Another example of preprocessing performed by the preprocessing module **114** is decoding a video frame file or a video file to extract the video frame **402** in a suitable image map format. In some examples, there is no preprocessing module **114** and preprocessing is not performed on the video frame **402**.

The processing unit(s) **111** returns a processing result, for example, the crowd motion data **404**, and the execution device **110** provides the processing result to the user equipment **140** via the I/O interface **112**. The processing result can include the video frame **402** or video (e.g., in native or compressed file format), or with the crowd motion data **404** overlaid on the video frame **402** or the video. The user equipment **140** can include a display screen that displays the crowd motion data **404**.

In another example, the user equipment **140** may transmit to the execution device **110**, via the I/O interface **112**, an identification of the video that contains the video frame **402** and causing the video containing the video frame **402** to be retrieved by the execution device **110** via I/O interface **112** (e.g. the user equipment **140** sending an identifier or an address of where to retrieve the video frame **402**).

In an example, each of the modules **101** can include a DNN. The DNN can also be referred to as a multi-layer neural network and may be understood as a neural network that includes a first layer (generally referred to as an input layer), a plurality of hidden layers, and a final layer (generally referred to as an output layer).

The DNN can be implemented by a Convolutional Neural Network (CNN), which is a deep neural network with a convolutional structure. The convolutional neural network includes a feature extractor consisting of a convolutional layer and a sub-sampling layer. The feature extractor may be considered as a filter. A convolution process may be considered as performing convolution on an image or a convolutional feature map (feature map) by using a trainable filter. The convolutional layer indicates a layer of neurons at which convolution processing is performed on an input in the convolutional neural network. At the convolutional layer of the convolutional neural network, one neuron may be connected only to neurons at some neighboring layers. One convolutional layer usually includes several feature maps, and each feature map may be formed by some neurons arranged in a rectangle. Neurons at a same feature map share a weight. The shared weight herein is the convolutional kernel. The shared weight may be understood as being unrelated to a manner and a position of image information extraction. A hidden principle is that statistical information of a part of an image is the same as that of another part. This indicates that image information learned in a part may also be used in another part. A plurality of convolutional kernels may be used at a same convolutional layer to extract different image information. Generally, a larger quantity of convolutional kernels indicates that richer image information is reflected by a convolution operation.

It should be noted that FIG. **1** is merely a schematic diagram of a system architecture of the crowd motion summarization system **100** according to an example embodiment. Position relationships between the execution device **110**, the user equipment **140**, the processing unit(s) **111**, the preprocessing module **114**, and the like that are shown in FIG. **1** do not constitute any limitation. For example, the data storage system **150** is an external memory relative to the execution device **110**. In another example, the data storage system **150** may be part of (i.e. located in) the execution device **110**.

As shown in FIG. **1**, in some examples, parts of the feature tracking module **101**A may be obtained through libraries, such as a KLT feature tracking model obtained from a library. Similarly, parts of the crowd occupancy detection module **101**B may be obtained through libraries, in which the library contains labelled images of humans or human heads.

FIG. **2** shows a block diagram of a neural network processor **200** implemented in the execution device according to an example embodiment. The computer chip may be provided in the execution device **110** shown in FIG. **1**, to perform computations of the models of the crowd motion summarization system **100**. The processing unit(s) **111** (FIG. **1**) can include a host CPU and the neural network processor **200**.

The neural network processor **200** may be any processor that is applicable to neural network computations, for example, a Neural Processing Unit (NPU), a tensor processing unit (TPU), a graphics processing unit (GPU), or the like. The NPU is used as an example. The NPU may be mounted, as a coprocessor, to the host CPU (Host CPU), and the host CPU allocates a task to the NPU. A core part of the NPU is an operation circuit **203**. A controller **204** controls the operation circuit **203** to extract matrix data from memories (input memory **201** and weight memory **202**) and perform multiplication and addition operations.

In some implementations, the operation circuit **203** internally includes a plurality of processing units (also known as a Process Engine, PE). In some implementations, the operation circuit **203** is a bi-dimensional systolic array. In addition, the operation circuit **203** may be a uni-dimensional systolic array or another electronic circuit that can implement a mathematical operation such as multiplication and addition. In some implementations, the operation circuit **203** is a general matrix processor.

For example, it is assumed that there are an input matrix A, a weight matrix B, and an output matrix C. The operation circuit **203** obtains, from a weight memory **202**, weight data of the matrix B, and caches the data in each PE in the operation circuit **203**. The operation circuit **203** obtains input data of the matrix A from an input memory **201**, and performs a matrix operation based on the input data of the matrix A and the weight data of the matrix B. An obtained partial or final matrix result is stored in an accumulator (accumulator) **208**.

A unified memory **206** is configured to store input data and output data. Weight data is directly moved to the weight memory **202** by using a storage unit access controller **205** (referred to as a Direct Memory Access Controller, DMAC). The input data is also moved to the unified memory **206** by using the DMAC.

A bus interface unit (BIU) **210** is used for interaction between the DMAC and an instruction fetch buffer **209** (memory). The bus interface unit **210** is further configured to enable the instruction fetch buffer **209** to obtain an instruction from an external memory, and is further configured to enable the storage unit access controller **205** to obtain, from the external memory, source data of the input matrix A or the weight matrix B.

The DMAC is mainly configured to move input data from an external memory Double Data Rate (DDR) to the unified memory **206**, or move the weight data to the weight memory **202**, or move the input data to the input memory **201**.

A vector computation unit **207** includes a plurality of operation processing units. If needed, the vector computation unit **207** performs further processing, for example, vector multiplication, vector addition, an exponent operation, a logarithm operation, or magnitude comparison, on an output from the operation circuit **203**. The vector computation unit **207** is mainly used for computation at a non-convolutional layer or fully-connected layers (FC, fully connected layers) of a neural network, and specifically, may perform processing on computation such as pooling (pooling) or normalization (normalization). For example, the vector computation unit **207** may apply a nonlinear function to an output of the operation circuit **203**, for example, a vector of an accumulated value, to generate an activation value. In some implementations, the vector computation unit **207** generates a normalized value, a combined value, or both a normalized value and a combined value.

In some implementations, the vector computation unit **207** stores a processed vector to the unified memory **206**. In some implementations, the vector processed by the vector computation unit **207** may be used as activation input to the operation circuit **203**, for example, to be used in a following layer of the neural network.

The instruction fetch memory **209** (Instruction Fetch Buffer) connected to the controller **204** is configured to store an instruction used by the controller **204**.

The unified memory **206**, the input memory **201**, the weight memory **202**, and the instruction fetch memory **209** are all on-chip memories. The external memory is independent from the hardware architecture of the NPU.

FIG. **3** illustrates an example of the crowd motion summarization system **100** which is configured to perform the crowd motion summarization method, according to an example embodiment. The crowd motion summarization method may be specifically performed by the feature tracking module **101**A, crowd occupancy detection module **101**B, feature-crowd matching module **101**C, and the data visualization module **101**D. The execution device **110** executes the crowd motion summarization method.

The crowd motion summarization method is used to process a video **400**. The video **400** include a plurality of video frames **402(1)**, **402(2)**, **402(3)**, . . . , **402**(N) (each video frame can be individually referred to as **402** or **402**(*n*)). The video **400** can be a video file having all of the video frames **402**, or the video **400** can be a streaming video in which video frames **402** are received individually or in batches. In the case of an indefinite streaming video, the last video frame **402**(N) is also indefinite. Each video frame **402** can be associated with time data, referred to as a time of the video frame **402**. The time of a video frame **402** can be a video frame number in a series of video frame numbers, or a time unit, or a clock time.

In the example shown, the video frame **402** is a birds eye view (BEV), which is an overhead perspective view. In other examples, the video frame **402** is an overhead view, an elevation view, or other such views with or without standard perspective effects.

The crowd motion summarization method starts with receiving the video frame **402**. An image file containing the video frame **402** in the crowd motion summarization method may be the input data provided by the camera **142** shown in FIG. **1**. In another example, the user equipment **140** sends the video frame **402** to the execution device **110** from memory of the user equipment **140**, e.g. as an image file or a video file. In another example, the user equipment **140** transmits a location of where the execution device **110** can access the video frame **402** (or the entire video **400**), e.g., a server, an Internet Protocol address, a social media account. The time of the video frame **402** is also received. The crowd motion data **404** is output by the crowd motion summarization method in which the crowd motion data **404** is visualized by way of tables, overlays on the video frame **402**, or summaries, etc.

The video frame **402** includes humans which are located by the crowd occupancy detection module **101**B of the execution device **110**. In an example, the crowd occupancy detection module **101**B identifies humans as one single category and identifies non-humans as another single category. The non-human category can include all non-human objects (which may be stationary or moving) and background.

From the video **400** and the crowd motion data **404**, the data visualization module **101**D of the execution device **110** can generate visualization data **420**.

The visualization data **420** of the crowd motion data **404** may still be referred to as crowd motion data **404** herein, and the terms can be used interchangeably depending on the example. For example, in some scenarios the visualization module **101**D of the execution device **110** merely passes (sends) the crowd motion data **404** to the user equipment **140**, and the user equipment **140** itself can have a visualization module **101**D which generates, from the crowd motion data **404**, the visualization data **420**.

FIG. **4** is an example crowd motion summarization method performed on a video frame **402** by the crowd motion summarization system **100**, according to an example embodiment. The crowd motion summarization method may be carried out by modules, routines, or subroutines of software executed by the processing unit(s) **111** of the execution device **110** or by the processing units of the user equipment **140**. Coding of software for carrying out the steps of crowd motion summarization method is well within the scope of a person of ordinary skill in the art having regard to the described crowd motion summarization method. The crowd motion summarization method may contain additional or fewer steps than shown and described, and the steps may be performed in a different order. Computer-readable instructions executable by the processor(s) of the execution device **110** or the user equipment **140** may be stored in memory of the execution device or the user equipment **140**, or a computer-readable medium. It is to be emphasized that the steps of the crowd motion summarization method need not be performed in the exact sequence as shown, unless otherwise indicated; and likewise various steps of the crowd motion summarization method may be performed in parallel rather than in sequence.

In an example scenario of the crowd motion summarization method, referring to FIG. **4**, the execution device **110** receives a first video frame **402(1)** of the video **400**. The execution device **110** uses the feature tracking module **101**A to detect features in the video frame **402(1)**. In an example, the features are feature points (also known as feature edge points, KLT corners or Harris corners) of visual features of particular edges detected from the video frame **402**(**1**).

The feature tracking module **101**A generates a filtered feature map. An example of the feature tracking module **101**A is illustrated in greater detail in FIG. **6** but summarized briefly here in relation to FIG. **4**. The feature tracking module **101**A generates, using the first video frame **402**(**1**): the feature location of each feature detected in the first video frame **402**(**1**). For example, the feature tracking module **101**A generates the feature points by way of a feature map which indicates each feature location of each feature as a pixel (edge point). In other examples, each generated feature location is represented by a Cartesian co-ordinate. The feature map (or feature location) can be temporarily stored in memory for comparison to a subsequent video frame (e.g. the second video frame **402**(**2**) in this example) for tracking of each detected feature of interest. In an example, at this stage, the feature tracking module **101**A does not consider whether the feature is part of a human or not. In an example, the feature tracking module **101**A includes a KLT feature tracking module, and the generated features are KLT features defined by KLT feature points (also known as KLT corners).

Continuing with the example, the crowd occupancy detection module **101**B generates, using the first video frame **402**(**1**): a binary crowd occupancy map **412** of the first video frame **402**(**1**) having human pixel positions which indicate the human location versus non-human location. The crowd occupancy detection module **101**B generates, using the first video frame **402**(**1**): a total human count of the humans detected in the video frame. An example of the crowd occupancy detection module **101**B is illustrated in greater detail in FIG. **5**. The binary crowd occupancy map **412** includes is to indicate human location and 0s to indicate non-human location. In an example, all other pixels that are not a human location are populated with 0s. Therefore, non-human moving objects which are distractors become populated in the binary crowd occupancy map **412** with 0s, e.g. moving cars, moving animals, clouds, swaying trees, etc. Therefore, in an example, the background of the video frame (**402**(**1**) is populated in the binary crowd occupancy map **412** with 0s, e.g. ground, buildings, sea and sky, etc.

Continuing with the example of FIG. **4**, the feature tracking module **101**A generates, using the feature map of the first video frame **402**(**1**) and the binary crowd occupancy map **412** of the first video frame **402**(**1**): a filtered feature map which contains the features for only those features that are in the human pixel positions for the first video frame **402**(**1**). For example, the feature tracking module **101**A generates the filtered feature map by performing element-wise multiplying (also known as Hadamard product) of the feature map and the binary crowd occupancy map **412**. Therefore, only the pixel locations of the features that correspond to human pixels remain in the filtered feature map.

Because there is no previous video frame for tracking purposes, in some examples crowd motion data **404** is not generated for the first video frame **402**(**1**) as there is nothing to compare. Rather, the next video frame **402** (i.e., a second video frame **402**(**2**)) in the video **400** can be processed by the execution device and compared to a filtered feature map of the first video frame **402**(**1**) to generate the crowd motion data **404**.

Continuing with the example in FIG. **4**, the execution device **110** receives a second video frame **402**(**2**) of the video **400**. The crowd occupancy detection module **101**B generates, using the second video frame **402**(**2**): human localization information **410** of humans detected in the second video frame **402**(**2**), and a binary crowd occupancy map **412** of the second video frame **402**(**2**) having human pixel positions which indicate the human location versus non-human location. The human localization information **410** can include: crowd density map of the second video frame **402**(**2**), and total human count in the second video frame **402**(**2**). An example of the crowd occupancy detection module **101**B is illustrated in greater detail in FIG. **5**.

The feature tracking module **101**A generates feature tracking information **408**, illustrated in greater detail in FIG. **6** but summarized briefly here. Continuing the example, the feature tracking module **101**A generates, using the second video frame **402**(**2**): a feature map including feature location of each feature (edge point) detected in the second video frame **402**(**2**). For example, the feature tracking module **101**A generates a feature map which indicates each feature location of each feature as a pixel. In some examples, each generated feature location is represented by a Cartesian co-ordinate.

Continuing the example of FIG. **4**, the feature tracking module **101**A generates, using the feature map of the second video frame **402**(**2**) and the binary crowd occupancy map **412** of the second video frame **402**(**2**): a filtered feature map which contains the feature tracking information **408** for only those features that are in the human pixel positions for the second video frame **402**(**2**). For example, the feature tracking module **101**A generates the filtered feature map by performing element-wise multiplication of the feature map and the binary crowd occupancy map. Therefore, only the pixel locations of the feature map that correspond to human pixels remain in the filtered feature map.

Continuing the example, the feature tracking module **101**A generates, using the second video frame **402**(**2**), the first video frame **402**(**1**), the filtered feature map of the second video frame **402**(**2**), and the filtered feature map of the first video frame **402**(**1**): feature tracking information **408** for each feature in the human pixel positions for the second video frame **402**(**2**), including: i) feature location, ii) feature speed, iii) feature orientation, iv) total feature count. In an example, the feature tracking module **101**A includes a KLT feature tracking module for detecting the same feature between the first video frame **402**(**1**) and the second video frame **402**(**2**), and generating the feature tracking information **408** of that feature (called KLT feature information).

In an example, the feature speed can be computed between a feature location of a feature in the second video frame **402**(**2**) and the feature location of the same feature in the first video frame **402**(**1**), and using a known time unit between the first video frame **402**(**1**) and the second video frame **402**(**2**). The feature orientation can be an angle computed between the feature location of the feature in the second video frame **402**(**2**) and the feature location of the same feature in the first video frame **402**(**1**). The feature orientation can be in degrees, radians, or other measurement units.

In the example of FIG. **4**, the feature-crowd matching module **101**C is configured to generate, using the feature tracking information **408** and the total human count: the crowd motion data **404**. The crowd motion data **404** includes: i) human speed count, ii) human orientation count, iii) total human count, and iv) time.

In an example, the feature-crowd matching module **101**C divides the total human count by the total feature count, arriving at an average number of features per human in the video frame **402**. The feature-crowd matching module **101**C generates (infers) the crowd motion data **404** from the average number of features per human and the feature tracking information. For example, if there are an average 5 features per human, then the feature-crowd matching module **101**C can infer from the feature tracking information that clusters of 5 features in the same orientation and speed can be inferred as being a human for the purposes of generating the crowd motion data **404**.

In an example, the generating of the crowd motion data **404** uses the feature tracking information **408** and total human count in the second video frame **402(2)**, and does not require particular knowledge of the previous crowd density map from the first video frame **402(1)**.

In the example of FIG. **4**, the execution device **110** can also loop to receive the third video frame **402(3)** of the video **400** and perform the crowd motion summarization method on the third video frame **402(3)** (including generating feature tracking information **408** by comparing to the second video frame **402(2)**), and so on.

In the example of FIG. **4**, the data visualization module **101**D generates, from the crowd motion data and the second video frame **402(2)**: visualization data **420**. In some examples, the data visualization module **101**D can directly receive the original video frame **402(2)** and the time. In other examples, the original second video frame **402(2)** and the time of the second video frame **402(2)** are transmitted (cascaded) through any of the modules **101** (i.e., the feature tracking module **101**A, the crowd occupancy detection module **101**B, or the feature-crowd matching module **101**C).

In some examples, the data visualization module **101**D generates a first overlay of the crowd motion data **404** that is overlaid on the first video frame **402(1)** or a second overlay of the crowd motion data **404** that is overlaid on the second video frame **402(2)** (and further overlays for further video frames **402**). In some examples, the data visualization module **101**D generates, for display on the same display screen, the first overlay of the first video frame **402(1)** and the second overlay of the second video frame **402(2)** (or further overlays).

In some examples, the data visualization module **101**D generates, from the crowd motion data **404**, the crowd motion data **404** in a form that can be visualized as the visualization data **420**, such as histograms, tables, summaries, charts, graphs, etc.

As shown in FIG. **3**, the visualization data **420** can include a histogram of motion summaries **406**, as follows: first histogram **406(1)** of human speed, time, human speed count; and second histogram **406(2)** of human orientation, time, human orientation count.

In some examples, the data visualization module **101**D detects an event from the crowd motion data **404**, and generates an event indication as an output that indicates occurrence of the event.

The data visualization module **101**D generates the crowd motion data **404** for the subsequent frames, e.g. third video frame **402(3)** and so on. The feature speed can be computed between a feature location of a feature in the third video frame **402(3)** and the feature location of the same feature in the second video frame **402(2)**, and using the known time unit between video frames. The feature orientation can be an angle computed between the feature location of the feature in the third video frame **402(3)** and the feature location of the same feature in the second video frame **402(2)**. The data visualization module **101**D generates crowd motion data **404** for the third video frame **402(3)**. In some examples, the feature speed and the feature orientation for the third video frame **402(2)** can be generated in relation to any of the previous video frames, e.g. versus the first video frame **402(1)** (e.g. to generate crowd motion data **404** of longer term trends or time-elapsed type analysis).

The crowd motion data **404** generated by the data visualization module **101**D can be displayed on a display screen or transmitted to the user equipment **140** in near real-time, as-needed, as soon as the crowd motion data **404** is generated for the third video frame **402(3)** and each subsequent video frame **402**(*n*).

The video frame **402** can be an image map which can contains humans and non-human objects. A pixel value of the video frame **402** may be a red, green, and blue (RGB) color value. The pixel value may be a long integer indicating a color. For example, a pixel value is 255*Red+100*Green+76*Blue, where Blue represents a bit shift of a blue component, Green represents a bit shift of a green component, and Red represents a bit shift of a red component. **255**, **100**, and **76** are the respective coefficients of Red, Green, and Blue. In a 24-bit color representation, Red is shifted by 16 bits (65,536) and Green is shifted by 8 bits (256), and Blue is shifted by 0 bits (1). In all the color components, a smaller coefficient indicates lower brightness, and a larger coefficient indicates higher brightness. For a grayscale image, the pixel value may be a grayscale value (e.g., 0 to 255). For a black and white image (binary map), the pixel value may be a binary value such as 0 and 1, or 0 and 255. In some examples, a mask image is generated from the video frame **402**, in which the mask image is a representation of one or more particular objects in the video frame **402** in which pixels of a particular object are filled in a single color, and the remaining pixels are white (zero). In some examples, a segmentation image (outline or edges) is generated from the video frame **402**, in which the outline image is a representation of one or more particular objects in the video frame **402** in which pixels of a particular object are defined with lines (outline or edges) in a single color, and the remaining pixels are white (zero).

FIG. **5** is an example detail flow diagram of human detection from the video frame **402** performed by the crowd occupancy detection module **101**B in accordance with an example embodiment. The crowd occupancy detection module **101**B includes a crowd density estimation module **502**, a human localization module **506**, a binary threshold module **508**, and a morphological transformation module **512**.

The execution device **110** receives a video frame **402** of the video **400**, such as the second video frame **402(2)** (FIG. **3**). The video frame **402** can also include time information. The crowd density estimation module **502** generates, using the video frame **402**, a crowd density map **504**. The crowd density map **504** includes pixels that each indicate a probability of the human location of a human detected in the video frame **402**. The sum total of probabilities in a cluster of pixels can be used to identify the probably that the cluster is a human.

The human localization module **506** generates, using the crowd density map **506**: the human localization information **410** of humans detected in the video frame **402**. The human localization information **410** can include: crowd density map of the video frame **402**, and total human count in the video frame **402**.

The binary threshold module **508** generates, from the crowd density map **504**: a threshold binary crowd occupancy map **510**. The binary threshold module **508** applies a threshold to the threshold binary crowd occupancy map **510**, and maintains pixels values of the crowd density map **504** that have a probability that exceeds the threshold. All other pixel locations are assigned a zero pixel value. Therefore, the threshold binary crowd occupancy map **510** has human pixels which indicate probable pixel positions of a human (or a human head in some examples).

The morphological transformation module **512** generates, from the threshold binary crowd occupancy map **510**: the binary crowd occupancy map **412**. The morphological transformation module **512** accounts for morphological human features of each human pixel of the threshold binary crowd occupancy map. For example, when only each human head is detected and indicated as a human pixel, the morphological transformation module **512** dilates the human pixel of the human head in order to account for the remainder of the body of the human. In an example, the morphological transformation module **512** includes a dilation module configured to dilate the human pixels which indicate the human location. For example, the dilation module can implement a convolution function with a M×M block (M>1) having values of 1 onto the threshold binary crowd occupancy map **510**. In other examples, a circle-shaped block having values of 1 is used for the convolution function. The dilation module also assists in creating a buffer so as to capture some addition pixels surrounding the human or the human head.

The binary crowd occupancy map **412** generated by the morphological transformation module **512** has human pixel positions which indicate the human location versus the non-human location. The binary crowd occupancy map **412** can be element-wise multiplied with the feature map to generate a filtered feature map, so that only the features relating to human pixel positions remain in the filtered feature map.

The crowd density estimation module **502** can include a human density estimation module. Other human or human head detection modules may be used in other examples, such as human instance segmentation models. The human or human head detection module can be trained with labelled images containing humans or human heads.

In an example, the crowd occupancy detection module **101**B (including the crowd density estimation module **502**, the human localization module **506**, the binary threshold module **508**, and the morphological transformation module **512**) do not require processing of the previous video frame or the previous human localization information **410** generated from the previous video frame. Rather, the crowd occupancy detection module **101**B can receive the video frame **402** as input without requiring input of the previous video frame or any previous human localization information **410**.

FIG. **6** is a detail flow diagram of feature tracking of the video frame **402** performed by the feature tracking module **101**A in accordance with an example embodiment. The feature tracking module **101**A is configured to detect features in the video frame **402**, such as feature points (also known as feature edge points, KLT corners or Harris corners) of visual features of particular edges detected from the video frame **402**(**1**). The feature tracking module **101**A is configured to generate the feature tracking information **408** of the detected features (feature points), including feature orientation and feature speed. In the example of FIG. **6**, the feature tracking module **101**A includes a KLT feature extraction module **602**, an element-wise multiplication module **606**, a KLT feature tracking module **610**, and a speed and orientation estimator module **614**.

The KLT feature extraction module **602** receives one of the video frames **402**, for example the second video frame **402**(**2**). The KLT feature extraction module **602** generates, from the video frame, a KLT feature map **604**. The KLT feature map **604** indicates each feature location of each KLT feature detected by the KLT feature extraction module **602** as a pixel (edge point). In other examples, each generated feature location is represented by a Cartesian co-ordinate.

Continuing with the example of FIG. **6**, the element-wise multiplication module **606** performs element-wise multiplication on the KLT feature map **604** and the binary crowd occupancy map **412**, generating a filtered KLT feature map **608**. Therefore, the KLT filtered feature map **608** contains the feature points for only those features that are in the human pixel positions for the video frame **402**. For example, the element-wise multiplication module **606** generates the filtered feature map by performing element-wise multiplication (also known as Hadamard product) of the KLT feature map **604** and the binary crowd occupancy map **412**. Therefore, only the pixel locations of the KLT feature map **604** that correspond to human pixels remain in the filtered KLT feature map **608**.

Note that a filtered KLT feature map **608** can also be previously generated for the first video frame **402**(**1**) in a similar manner, denoted first filtered KLT feature map **608**. The filtered KLT feature map **608** for the second video frame **402**(**2**) is denoted second filtered KLT feature map **608**.

Continuing the example, the KLT feature tracking module **610** generates, using the first video frame **402**(**1**), the second video frame **402**(**2**), the first filtered KLT feature map **608** of the first video frame **402**(**1**), and the second filtered KLT feature map **608** of the second video frame **402**(**2**): feature tracklets **612** for each feature detected in the second video frame **402**(**2**). Feature tracklets are vectors (directed line segments) between the feature point of the first filtered KLT feature map **608** and the same feature point detected in the second filtered KLT feature map **608**. Each feature tracklet can be in the form of a vector or an ordered pair of Cartesian co-ordinates, and can be visualized as a vector line segment on the original video frame **402**.

The speed and orientation estimator module **614** is used to generate feature tracking information **408** from the feature tracklets **612**, for each feature in the human pixel positions for the second video frame **402**(**2**). The tracking information includes: i) feature location, ii) feature speed, iii) feature orientation and iv) total feature count. The feature location is the feature location in the second video frame **402**(**2**) in this example.

In an example, the feature speed can be computed between the two feature locations of each tracklet (vector) in the feature tracklets **612**, and optionally using a known time unit between the first video frame **402**(**1**) and the second video frame **402**(**2**). In an example, the feature speed for the i^{th} feature is calculated as:

$$M^i = \sqrt{(x_n^i - x_{n-1}^i)^2 + (y_n^i - y_{n-1}^i)^2}, \quad \text{(Equation 1)}$$

wherein (x, y) are Cartesian co-ordinates of the feature location for the i^{th} feature, n is the subject video frame (second video frame **402**(**2**) in this example), and n−1 is the previous video frame (first video frame **402**(**1**) in this example).

The feature orientation can be an angle computed between the two feature locations of each tracklet (vector) in the feature tracklets **612**. The feature orientation can be in degrees, radians, or other measurement units. In an example, the feature orientation for an i^{th} feature is calculated as:

$$\theta^i = \arctan\frac{(y_n^i - y_{n-1}^i)}{(x_n^i - x_{n-1}^i)}, \quad \text{(Equation 2)}$$

wherein (x, y) are Cartesian co-ordinates of the feature location for the i^{th} feature, n is the subject video frame, and n−1 is the previous video frame.

Referring again to FIG. **4**, the feature-crowd matching module **101**C matches human localization information with the detected features. In the example of FIG. **4**, the feature-crowd matching module **101**C is configured to generate, using the feature tracking information **408** and the total human count: the crowd motion data **404**. The crowd motion data **404** includes: i) human speed count, ii) human orientation count, iii) total human count, and iv) time. In an example, the feature-crowd matching module **101**C divides the total human count by the total feature count, arriving at an average number of features per human in the second video frame **402**(**2**). In an example, the feature-crowd matching module **101**C generates (infers) the number of features per human. The feature-crowd matching module **101**C generates (infers) the crowd motion data **404** from the number of features per human and the feature tracking information.

FIG. **7** is a detail pictorial representation of maps, data and information generated by each module of the crowd motion summarization system **100**, in accordance with an example embodiment. The crowd density estimation module **502** receives the video frame **402** and time information of the video frame **402**. For example, the video frame **402** is the second video frame **402**(**2**). The crowd density estimation module **502** generates, using the video frame **402**: the crowd density map **504**. The crowd density map **504** includes pixels that each indicate a probability of the human location of a human detected in the video frame **402**.

The human localization module **506** generates, using the crowd density map **504**: the human localization information **410** of humans detected in the video frame **402**. The human localization information **410** can include the total human count and the crowd density map **504**.

The binary threshold module **508** generates, from the crowd density map **504**, the threshold binary crowd occupancy map **510**. The binary threshold module **508** applies a threshold to the threshold binary crowd occupancy map **510**, and maintains pixels values of the crowd density map **504** that have a probability that exceeds the threshold. All other pixel locations are assigned a zero pixel value.

The morphological transformation module **512** generates, from the threshold binary crowd occupancy map **510**, the binary crowd occupancy map **412** which includes human pixel positions which indicate the human location. For example, the morphological transformation module **512** includes a dilation module configured to dilate the human pixels which indicate the human location.

The KLT feature extraction module **602** of the feature tracking module **101**A is configured to detect features in the video frame **402**, such as feature points, and generate the KLT feature map **604**.

The element-wise multiplication module **606** performs element-wise multiplication on the KLT feature map **604** and the binary crowd occupancy map **412**, generating the filtered KLT feature map **608**. Therefore, the KLT filtered feature map **608** contains the feature points for only those features that are in the human pixel positions for the video frame **402**.

Note that the first filtered KLT feature map **608** can also be previously generated for the first video frame **402**(**1**) in a similar manner, not shown here. The KLT feature tracking module **610** generates, using the first video frame **402**(**1**), the second video frame (**402**(**2**)), a first filtered KLT feature map **608** (not shown here) of the first video frame **402**(**1**), and the second filtered KLT feature map **608** of the second video frame **402**(**2**): feature tracklets **612** for each feature detected in the second video frame **402**(**2**). Each feature tracklet can be a vector line segment, in which the feature tracklets **612** can be overlaid on the original second video frame **402**(**2**), as shown in FIG. **7**.

The speed and orientation estimator module **614** is used to generate feature tracking information **408** from the feature tracklets **612**, including: i) feature location, ii) feature speed, and iii) feature orientation, and iv) total feature count. The feature location is the feature location in the second video frame **402**(**2**) in this example.

Continuing with the example of FIG. **7**, the feature-crowd matching module **101**C matches human localization information with the detected features. In the example of FIG. **4**, the feature-crowd matching module **101**C is configured to generate, using the feature tracking information **408** and the total human count: the crowd motion data **404**. The crowd motion data includes: i) human speed count, ii) human orientation count, iii) total human count, and iv) time. In an example, the feature-crowd matching module **101**C divides the total human count by the total feature count, arriving at an average number of features per human in the video frame **402**. The feature-crowd matching module **101**C generates (infers) the crowd motion data **404** from the average number of features per human and the feature tracking information.

The data visualization module **101**D generates the visualization data **420** from the crowd motion data **404**.

FIG. **8** is a schematic diagram of the data visualization module **101**D, in accordance with an example embodiment. The data visualization module **101**D receives the crowd motion data **404**, which includes: i) human speed count, ii) human orientation count, iii) total human count, and iv) time. The data visualization module **101**D also receives the video frame **402** and (optionally) the time of the video frame **402**, either directly or are transmitted (cascaded) through any of the modules **101** (feature tracking module **101**A, crowd occupancy detection module **101**B, or feature-crowd matching module **101**C).

The data visualization module **101**D generates the visualization data **404** from the crowd motion data **404**. The visualization data **404** can also include the crowd motion data **404**. In some examples, the data visualization module **101**D also includes a table generator module **804**, a video frame overlay module **806**, and an event detection module **808**.

In some examples, the table generator module **804** generates histograms, tables, summaries, charts, graphs, etc., from the crowd motion data **404** (or the visualization data **404**, which can be interchangeably used depending on the configuration). As shown in FIG. **8**, the table generator module **804** can generate a histogram of motion summaries **406**, which is illustrated in FIG. **9**. As shown in FIG. **9**, the histogram of motion summaries **406** includes: first histogram **406**(**1**) of human speed **902**, time **904**, human speed count **906**; and second histogram **406**(**2**) of human orientation **908**, time **910**, human orientation count **912**. In some examples, the histogram of motion summaries **406** is generated such that the first histogram **406**(**1**) and the second histogram **406**(**2**) are displayed by the user equipment **140** on the same display screen. In some examples, the histogram of motion summaries **406** is generated, updated and displayed by the user equipment **140** in near real-time, as-needed, as more video frames **402** are received by the crowd motion summarization method and more crowd motion data **404** is received by the data visualization module **101**D.

The histogram of motion summaries **406** combines crowd motion and person counts to create a rich descriptor for crowds in the video **400**. The histogram of motion summaries **40** amenable to a number of applications, including: i) crowd anomaly detection for public safety (e.g., stampeding, diverging, converging, sudden changes in speed/direction, crowd panic, moving in wrong direction, sudden changes in crowd size); ii) unauthorized access (e.g., detecting non-zero person counts in out-of-bounds areas); iii) congestion control (e.g., overcrowding prevention); iv) attendance analytics (e.g., number of people attending an event, performance, or concert); and v) shopping analytics and store design (e.g., crowd counts, dwell times, and movement speeds adjacent to various products and advertisements).

In the example of FIG. **8**, the video frame overlay module **806** generates, from the crowd motion data **404**, an overlay **810** of the crowd motion data **404** that is overlaid on the video frame **402**, such as the second video frame **402**(**2**) (and further overlays **810** for further video frames **402**(n)). In some examples, the overlay **810** generated by the overlay module **806** can be separate data or metadata of the video frame **402**, or in other examples can be overlaid on the video frame **402** and generated (saved) as a new video frame file.

FIG. **10** illustrates an example of the overlay on the video frame **402** generated by the data visualization module **101**D. A first overlay **810**(**1**) is displayed on the video frame **402**, which illustrates the feature tracklets **612** (FIG. **6**) in the subject video frame **402**. The feature tracklets **612** are only those of humans, and not other non-human objects or background. Therefore, other non-human features or features of non-human moving distractors are not generated in the first overlay **810**(**1**).

FIG. **10** also illustrates a second overlay **810**(**2**) displayed on the video frame **402**, which illustrates the total human count and total human orientation for particular segments of the video frame **402**. For example, the video frame **402** can be segmented into 3×2 segments in the present example. The size and number of the particular segments can be manually set in some examples. In other examples, the particular segments are generated by a data visualization model. The second overlay **810**(**2**) includes large arrows which indicate the human speed count and the human orientation count at the particular segments of the video frame **402**.

In the example of FIG. **8**, the event detection module **808** generates an event indication **812** from the crowd motion data **404**. In some examples, the event indication **812** as output to the user equipment **140**, and the user equipment **140** is configured to output (e.g., through the display screen, a speaker, or a transmission) the event indication **812**. Examples of the event indication **812** are described next in relation to FIGS. **11**A, **11**B, **11**C and **11**D.

FIG. **11**A illustrates an example of two sequential video frames overlaid with crowd motion data **404** representing crowd panic detection, generated by the data visualization module **101**D. The event detection module **808** generates, from the crowd motion data **404**, an event indication **812** of crowd panic detection. The video frame overlay module **806** generates, from the crowd motion data **404**, a first overlay of a subject video frame **402**(n) and a second overlay of subsequent video frame **402**(n+1), in which the subsequent video frame **402**(n+1) is subsequent to the subject video frame **402**(n). The first overlay and the second overlay both include feature tracklets. The table generator module **804** generates a first table **1100** of the crowd motion data **404** of the subject video frame **402**(n) and a second table **1102** of the crowd motion data of the subsequent video frame **402**(n+1). The event detection module **808** generates, from the crowd motion data **404**, the event indication **812** of crowd panic detection when the orientation (direction) of the humans is scattered and the speed count increases for a higher speed. Scatters means the humans are moving away from a particular position.

In FIG. **11**A, the first table **1100** of the subject video frame **402**(n) shows a speed of 3 pixels/frame and a speed count for the 3 pixels/frame is 12 humans, and the orientation is random. The second table **1102** of the subsequent video frame **402**(n+1) shows an increased speed of 7 pixels/frame and a speed count for the 2 pixels/frame of 11 humans, and the orientation is scatter.

FIG. **11**B illustrates an example of two sequential video frames overlaid with crowd motion data representing crowd moving in wrong direction detection, generated by the data visualization module **101**D. The event detection module **808** generates, from the crowd motion data **404**, an event indication **812** of the crowd moving in wrong direction detection. The video frame overlay module **806** generates, from the crowd motion data **404**, a first overlay of a subject video frame **402**(n) and a second overlay of subsequent video frame **402**(n+1), in which the subsequent video frame **402** (n+1) is subsequent to the subject video frame **402**(n). The first overlay and the second overlay each include feature tracklets. The table generator module **804** generates a first table **1100** of the crowd motion data **404** of the subject video frame **402**(n) and a second table **1102** of the crowd motion data **404** of the subsequent video frame **402**(n+1). The event detection module **808** generates, from the crowd motion data **404**, the event indication **812** of crowd moving in wrong direction detection when the orientation (direction) of the humans is generally in the opposite orientation as the original video frame **402**(n).

In FIG. **11**B, the first table **1100** of the subject video frame **402**(n) shows a speed of 2 pixels/frame and a speed count for the 2 pixels/frame is 164 humans. The second table **1102** of the subsequent video frame **402**(n+1) shows a speed of 2 pixels/frame and a speed count for the 2 pixels/frame of 167 humans.

FIG. **11**C illustrates an example of two sequential video frames overlaid with crowd motion data representing crowd stampede detection, generated by the data visualization module **101**D. The event detection module **808** generates, from the crowd motion data **404**, an event indication **812** of the crowd stampede detection. The video frame overlay module **806** generates, from the crowd motion data **404**, a first overlay of a subject video frame **402**(n) and a second overlay of subsequent video frame **402**(n+1), in which the subsequent video frame **402**(n+1) is subsequent to the subject video frame **402**(n). The first overlay and the second overlay both include feature tracklets. The table generator module **804** generates a first table **1100** of the crowd motion data **404** of the subject video frame **402**(n) and a second table **1102** of the crowd motion data **404** of the subsequent video frame **402**(n+1). The event detection module **808** generates, from the crowd motion data **404**, the event indication **812** of crowd stampede detection when the speed count of a high speed of the humans increases within a short time, all in a single orientation (direction). The first table **1100** of the subject video frame **402**(n) shows a speed of **0**. Note that the feature tracklet for a speed of zero in the first overlay can be represented by a dot, rather than a vector line segment. The second table **1102** of the subsequent video frame **402**(n+1) shows a speed of 11 pixels/frame and a speed count for the 11 pixels/frame is 277 humans. An example of crowd stampede detection is the start of a running race.

FIG. **11**D illustrates an example of two sequential video frames overlaid with crowd motion data **404** representing localized unusual crowd motion detection, generated by the data visualization module **101**D. The event detection module **808** generates, from the crowd motion data **404**, an event indication **812** of the localized unusual crowd motion detection. FIG. **11**D illustrates the total human count and total human orientation for particular segments of the video frame **402**. For example, the video frame **402** can be segmented into 3×3 segments in the present example. The segments are labeled R**1** to R**9** in the present example. The size and number of the particular segments can be manually set in some examples. In other examples, the particular segments are generated by a data visualization model.

The video frame overlay module **806** generates, from the crowd motion data **404**, a first overlay of a subject video frame **402**(n) and a second overlay of subsequent video frame **402**(n+1), in which the subsequent video frame **402**(n+1) is subsequent to the subject video frame **402**(n). The first overlay and the second overlay both include feature tracklets. The table generator module **804** generates a first table **1104** of the crowd motion data **404** of the subject video frame **402**(n) and a second table **1106** of the crowd motion data of the subsequent video frame **402**(n+1). The event detection module **808** generates, from the crowd motion data **404**, the event indication **812** of localized unusual crowd motion detection when the orientation (direction) of the humans in one of the segments is generally in the opposite orientation as the original video frame **402**(n). In the present example, the crowd motion data **404** of the original video frame **402**(n) is generally the humans moving in an orientation of a counter-clockwise direction. In the present example, there is localized unusual crowd motion detection in segments R**4**, R**6**, R**7**, R**8** and R**9** of the subsequent video frame **402**(n+1).

It would be appreciated that the described crowd motion summarization system and crowd motion summarization method can be used for different levels of crowd density, different crowd group sizes, camera placements, and standard perspective effects.

The crowd motion summarization system and crowd motion summarization method can be used in a variety of applications. For example, there are numerous traffic cameras around the world and there are numerous roads and traffic intersections that could benefit from the crowd motion summarization method.

There are roughly 500 cities with a population over 1 million, where the crowd motion summarization method would benefit the municipalities (e.g., public safety, urban planning).

There are more than 10,000 airports in the world that offer jet-based passenger services that could use AI enhanced cameras for crowd management in view of the crowd motion data provided by the crowd motion summarization method.

There are over 250 shopping malls with at least 100,000 m^2 of gross leasable area, where cameras enabled with the crowd motion summarization method could assist with store design to increase profits.

There are over 500 stadiums and 250 indoor arenas in the world with seating capacities over 40,000 and 15,000, respectively, where smart cameras enabled with the crowd motion summarization method could be used for ensuring crowd safety.

The user equipment **140** can be a remote terminal in a remote location to the camera **142**. The remote terminal can have one or more display screens for displaying crowd motion data of one or more of the cameras **142**. Other examples of the user equipment **140** can be used for crowd control, consumer traffic summarizing, hospital emergency room traffic summarizing, infrastructure construction planning, smart city movement summarizing, etc.

It should be understood by a person skilled in the art that, for the purpose of convenient and brief description, for a detailed working process of the foregoing system, apparatus, and unit, refer to a corresponding process in the foregoing method embodiments, and details are not described herein again.

In the several embodiments described, it should be understood that the disclosed system, apparatus, and method may be implemented in other manners. For example, the described apparatus embodiment is merely an example. For example, the unit division is merely logical function division and may be other division in actual implementation. For example, a plurality of units or components may be combined or integrated into another system, or some features may be ignored or not performed. In addition, the displayed or discussed mutual couplings or direct couplings or communication connections may be implemented by using some interfaces. The indirect couplings or communication connections between the apparatuses or units may be implemented in electronic, mechanical, or other forms.

The units described as separate parts may or may not be physically separate, and parts displayed as units may or may not be physical units, may be located in one position, or may be distributed on a plurality of network units. Some or all of the units may be selected according to actual requirements to achieve the objectives of the solutions of the embodiments.

In addition, functional units in the example embodiments may be integrated into one processing unit, or each of the units may exist alone physically, or two or more units are integrated into one unit.

When the functions are implemented in the form of a software functional unit and sold or used as an independent product, the functions may be stored in a non-transitory computer-readable storage medium. Based on such an understanding, the technical solutions may be implemented in a form of a software product. The software product is stored in a storage medium, and includes several instructions for instructing user equipment or a computer device to perform all or some of the steps of the methods described in the example embodiments. The foregoing storage medium includes any medium that can store program code, such as a Universal Serial Bus (USB) flash drive, a removable hard disk, a read-only memory (Read-Only Memory, ROM), a random access memory (Random Access Memory, RAM), a magnetic disk, or an optical disc.

The foregoing descriptions are merely specific implementations, but are not intended to limit the scope of protection. Any variation or replacement readily figured out by a person skilled in the art within the technical scope shall fall within the scope of protection. Therefore, the scope of protection shall be subject to the protection scope of the claims.

What is claimed is:

1. A crowd motion summarization method, comprising:

receiving a video frame;

generating, using a crowd occupancy detection module and the video frame: a binary crowd occupancy map of the video frame having human pixel positions which indicate human location versus non-human location, and a total human count of humans detected in the video frame, the generating the binary crowd occupancy map including:

generating, using a crowd density estimating module and the video frame: a crowd density map which includes a probability of the human location,

generating, using a binary threshold module and the crowd density map: a threshold binary crowd occupancy map of the crowd density map for the probability that exceeds a threshold, the threshold binary crowd occupancy map having the human pixel positions which indicate the human location versus the non-human location, and

generating, using a morphological transformation module and the threshold binary crowd occupancy map: the binary crowd occupancy map from the threshold binary crowd occupancy map which accounts for morphological human features;

generating, using a feature tracking module and the video frame: a feature map including feature location of features detected in the video frame;

generating, using the feature tracking module, the feature map, the binary crowd occupancy map, the video frame, a previous video frame, and previous feature location of previous features detected from the previous video frame: feature tracking information for only each feature in the human pixel positions for the video frame, including: i) the feature location, ii) feature speed, iii) feature orientation, and iv) total feature count; and

generating, using a feature-crowd matching module, the feature tracking information, and the total human count: crowd motion data including: i) a human speed count of at least one human speed, ii) a human orientation count of at least one human orientation.

2. The crowd motion summarization method as claimed in claim 1, wherein the crowd motion data further includes: iii) time of the video frame, the method further comprising generating, using a data visualization module and the crowd motion data: visualization data of the crowd motion data.

3. The crowd motion summarization method as claimed in claim 2, further comprising generating, using the data visualization module: the visualization data including at least one table which includes the human speed count and the human orientation count.

4. The crowd motion summarization method as claimed in claim 2, further comprising generating, using the data visualization module: the visualization data including at least one table which includes: i) the human speed count, ii) the human orientation count, and iii) the time of the video frame.

5. The crowd motion summarization method as claimed in claim 4, further comprising generating the visualization data for at least one other video frame, wherein the at least one table further includes: a first histogram of the human speed count, the human speed, and the time, and a second histogram of the human orientation count, the human orientation, and the time.

6. The crowd motion summarization method as claimed in claim 2, further comprising generating, using the data visualization module and the video frame: a first overlay of the video frame with the crowd motion data overlaid on the video frame.

7. The crowd motion summarization method as claimed in claim 6, further comprising generating, using the data visualization module and the previous video frame: a second overlay of the previous video frame with previous crowd motion data overlaid on the previous video frame; and generating the crowd motion data to display the first overlay and the second overlay on a same display screen.

8. The crowd motion summarization method as claimed in claim 2, wherein the generating the crowd motion data is performed in near real-time when the video frame is received.

9. The crowd motion summarization method as claimed in claim 1, wherein the morphological transformation module includes a dilation module configured to dilate the human pixel positions which indicate the human location.

10. The crowd motion summarization method as claimed in claim 1, wherein the features are Kanade-Lucas-Tomasi (KLT) features, wherein the feature tracking information includes KLT feature tracking information, wherein the feature locations are KLT feature locations, wherein the generating the feature tracking information includes:

generating, using a KLT feature extraction module and the video frame: a KLT feature map of KLT feature location of the KLT features detected in the video frame;

generating, by element-wise multiplying of the KLT feature map with the binary crowd occupancy map: a filtered KLT feature map with only the KLT feature locations in the human pixel positions for the video frame;

generating, using a KLT feature tracking module: a respective feature tracklet between the KLT feature location of each KLT feature and a previous KLT feature location detected from the previous video frame; and

generating, using a speed and orientation estimator module and the respective feature tracklet: the feature tracking information for each KLT feature, including: KLT feature speed, and KLT feature orientation.

11. The crowd motion summarization method as claimed in claim 1, wherein the features are KLT features, and wherein the feature tracking information includes KLT feature tracking information.

12. The crowd motion summarization method as claimed in claim 1, wherein the generating using the feature-crowd matching module includes estimating a number of the features per human.

13. The crowd motion summarization method as claimed in claim 1:

wherein the feature orientation for an i^{th} feature is calculated as:

$$\theta^i = \arctan\frac{(y_n^i - y_{n-1}^i)}{(x_n^i - x_{n-1}^i)};$$

and

wherein the feature speed for the i^{th} feature is calculated as:

$$M^i = \sqrt{(x_n^i - x_{n-1}^i)^2 + (y_n^i - y_{n-1}^i)^2},$$

wherein (x, y) are Cartesian co-ordinates of the feature location for the i^{th} feature, n is the video frame, and n−1 is the previous video frame.

14. The crowd motion summarization method as claimed in claim **1**, further comprising:

receiving the previous video frame; and

generating, using the feature tracking module, for each previous feature detected in the previous video frame: the previous feature location.

15. The crowd motion summarization method as claimed in claim **14**, further comprising:

generating, using the crowd occupancy detection module and the previous video frame: a previous binary crowd occupancy map of the previous video frame having the human pixel positions which indicate the human location versus the non-human location; and

wherein the generating the previous feature location is performed on only each feature in the human pixel positions of the previous binary crowd occupancy map for the previous video frame.

16. The crowd motion summarization method as claimed in claim **1**, wherein the generating the binary crowd occupancy map uses the video frame without using any previous video frame or any previous binary crowd occupancy map.

17. The crowd motion summarization method as claimed in claim **1**:

wherein the crowd occupancy detection module includes a crowd occupancy detection model; and

wherein the feature tracking module includes a feature tracking model.

18. The crowd motion summarization method as claimed in claim **1**, wherein the method is performed by at least one processor.

19. A crowd motion summarization apparatus, comprising:

memory; and

at least one processor configured to execute instructions stored in the memory, to:

receive a video frame,

generate, using a crowd occupancy detection module and the video frame: a binary crowd occupancy map of the video frame having human pixel positions which indicate human location versus non-human location, and a total human count of humans detected in the video frame, the generating the binary crowd occupancy map including:

generating, using a crowd density estimating module and the video frame: a crowd density map which includes a probability of the human location,

generating, using a binary threshold module and the crowd density map: a threshold binary crowd occupancy map of the crowd density map for the probability that exceeds a threshold, the threshold binary crowd occupancy map having the human pixel positions which indicate the human location versus the non-human location, and

generating, using a morphological transformation module and the threshold binary crowd occupancy map: the binary crowd occupancy map from the threshold binary crowd occupancy map which accounts for morphological human features,

generate, using a feature tracking module and the video frame: a feature map including feature location of features detected in the video frame,

generate, using the feature tracking module, the feature map, the binary crowd occupancy map, the video frame, a previous video frame, and previous feature location of previous features detected from the previous video frame: feature tracking information for only each feature in the human pixel positions for the video frame, including: i) the feature location, ii) feature speed, iii) feature orientation, and iv) total feature count, and

generate, using a feature-crowd matching module, the feature tracking information, and the total human count: crowd motion data including: i) a human speed count of at least one human speed, ii) a human orientation count of at least one human orientation.

20. A non-transitory computer-readable medium including instructions executable by at least one processor, the instructions comprising:

instructions for receiving a video frame;

instructions for generating, using a crowd occupancy detection module and the video frame: a binary crowd occupancy map of the video frame having human pixel positions which indicate human location versus non-human location, and a total human count of humans detected in the video frame, the instructions for generating the binary crowd occupancy map including:

instructions for generating, using a crowd density estimating module and the video frame: a crowd density map which includes a probability of the human location,

instructions for generating, using a binary threshold module and the crowd density map: a threshold binary crowd occupancy map of the crowd density map for the probability that exceeds a threshold, the threshold binary crowd occupancy map having the human pixel positions which indicate the human location versus the non-human location, and

instructions for generating, using a morphological transformation module and the threshold binary crowd occupancy map: the binary crowd occupancy map from the threshold binary crowd occupancy map which accounts for morphological human features;

instructions for generating, using a feature tracking module and the video frame: a feature map including feature location of features detected in the video frame;

instructions for generating, using the feature tracking module, the feature map, the binary crowd occupancy map, the video frame, a previous video frame, and previous feature location of previous features detected from the previous video frame: feature tracking information for only each feature in the human pixel positions for the video frame, including: i) the feature location, ii) feature speed, iii) feature orientation, and iv) total feature count; and

instructions for generating, using a feature-crowd matching module, the feature tracking information, and the total human count: crowd motion data including: i) a human speed count of at least one human speed, ii) a human orientation count of at least one human orientation.

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